

Sri Sivasubramaniya Nadar College of Engineering, Chennai
(An autonomous Institution affiliated to Anna University)

Degree & Branch	B.E. Computer Science & Engineering	Semester VI
Subject Code & Name	UCS2612 – Machine Learning Algorithms Laboratory	
Academic Year	2025–2026 (Even)	Batch 2023–2027
Due Date	27.01.2026	

Experiment 2: Binary Classification using Naïve Bayes and K-Nearest Neighbors

Objective

To implement Naïve Bayes and K-Nearest Neighbors (KNN) classifiers for a binary classification problem, evaluate them using multiple performance metrics, visualize model behavior, and analyze overfitting, underfitting, and bias-variance characteristics.

Dataset

A benchmark binary classification dataset containing numerical features and two class labels is used.

Dataset reference:

- Kaggle: [Spambase Dataset](#)

```
[23]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import time
import math
from matplotlib import rcParams
from sklearn.model_selection import train_test_split, StratifiedKFold,
↳GridSearchCV, RandomizedSearchCV, cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,
↳f1_score, confusion_matrix, roc_curve, auc
rcParams['font.family']='Arial'
rcParams['font.weight']='bold'
rcParams['font.size']=15
rcParams['axes.labelweight']='bold'
rcParams['axes.titleweight']='bold'
rcParams['xtick.labelsize']=15
rcParams['ytick.labelsize']=15
```

```
from sklearn.metrics import (
accuracy_score, precision_score, recall_score, f1_score,
confusion_matrix, classification_report, roc_auc_score,
roc_curve, average_precision_score)
```

```
[18]: #Load the dataset
df=pd.read_csv('spambase_csv_Kaggle.csv')
df
```

```
[18]:
```

	word_freq_make	word_freq_address	word_freq_all	word_freq_3d	\
0	0.00	0.64	0.64	0.0	
1	0.21	0.28	0.50	0.0	
2	0.06	0.00	0.71	0.0	
3	0.00	0.00	0.00	0.0	
4	0.00	0.00	0.00	0.0	
...	
4596	0.31	0.00	0.62	0.0	
4597	0.00	0.00	0.00	0.0	
4598	0.30	0.00	0.30	0.0	
4599	0.96	0.00	0.00	0.0	
4600	0.00	0.00	0.65	0.0	

	word_freq_our	word_freq_over	word_freq_remove	word_freq_internet	\
0	0.32	0.00	0.00	0.00	
1	0.14	0.28	0.21	0.07	
2	1.23	0.19	0.19	0.12	
3	0.63	0.00	0.31	0.63	
4	0.63	0.00	0.31	0.63	
...	
4596	0.00	0.31	0.00	0.00	
4597	0.00	0.00	0.00	0.00	
4598	0.00	0.00	0.00	0.00	
4599	0.32	0.00	0.00	0.00	
4600	0.00	0.00	0.00	0.00	

	word_freq_order	word_freq_mail	...	char_freq_%3B	char_freq_%28	\
0	0.00	0.00	...	0.000	0.000	
1	0.00	0.94	...	0.000	0.132	
2	0.64	0.25	...	0.010	0.143	
3	0.31	0.63	...	0.000	0.137	
4	0.31	0.63	...	0.000	0.135	
...	
4596	0.00	0.00	...	0.000	0.232	
4597	0.00	0.00	...	0.000	0.000	
4598	0.00	0.00	...	0.102	0.718	
4599	0.00	0.00	...	0.000	0.057	

4600	0.00	0.00	...	0.000	0.000
------	------	------	-----	-------	-------

	char_freq_%5B	char_freq_%21	char_freq_%24	char_freq_%23	\
0	0.0	0.778	0.000	0.000	
1	0.0	0.372	0.180	0.048	
2	0.0	0.276	0.184	0.010	
3	0.0	0.137	0.000	0.000	
4	0.0	0.135	0.000	0.000	
...	
4596	0.0	0.000	0.000	0.000	
4597	0.0	0.353	0.000	0.000	
4598	0.0	0.000	0.000	0.000	
4599	0.0	0.000	0.000	0.000	
4600	0.0	0.125	0.000	0.000	

	capital_run_length_average	capital_run_length_longest	\
0	3.756	61	
1	5.114	101	
2	9.821	485	
3	3.537	40	
4	3.537	40	
...	
4596	1.142	3	
4597	1.555	4	
4598	1.404	6	
4599	1.147	5	
4600	1.250	5	

	capital_run_length_total	class
0	278	1
1	1028	1
2	2259	1
3	191	1
4	191	1
...
4596	88	0
4597	14	0
4598	118	0
4599	78	0
4600	40	0

[4601 rows x 58 columns]

```
[7]: #Perform Exploratory Data Analysis (EDA)
df.describe()
```

```

[7]:      word_freq_make  word_freq_address  word_freq_all  word_freq_3d  \
count      4601.000000      4601.000000      4601.000000      4601.000000
mean        0.104553        0.213015        0.280656        0.065425
std         0.305358        1.290575        0.504143        1.395151
min         0.000000        0.000000        0.000000        0.000000
25%         0.000000        0.000000        0.000000        0.000000
50%         0.000000        0.000000        0.000000        0.000000
75%         0.000000        0.000000        0.420000        0.000000
max         4.540000        14.280000        5.100000        42.810000

      word_freq_our  word_freq_over  word_freq_remove  word_freq_internet  \
count      4601.000000      4601.000000      4601.000000      4601.000000
mean        0.312223        0.095901        0.114208        0.105295
std         0.672513        0.273824        0.391441        0.401071
min         0.000000        0.000000        0.000000        0.000000
25%         0.000000        0.000000        0.000000        0.000000
50%         0.000000        0.000000        0.000000        0.000000
75%         0.380000        0.000000        0.000000        0.000000
max        10.000000        5.880000        7.270000        11.110000

      word_freq_order  word_freq_mail  ...  char_freq_%3B  char_freq_%28  \
count      4601.000000      4601.000000  ...      4601.000000      4601.000000
mean        0.090067        0.239413  ...        0.038575        0.139030
std         0.278616        0.644755  ...        0.243471        0.270355
min         0.000000        0.000000  ...        0.000000        0.000000
25%         0.000000        0.000000  ...        0.000000        0.000000
50%         0.000000        0.000000  ...        0.000000        0.065000
75%         0.000000        0.160000  ...        0.000000        0.188000
max         5.260000        18.180000  ...        4.385000        9.752000

      char_freq_%5B  char_freq_%21  char_freq_%24  char_freq_%23  \
count      4601.000000      4601.000000      4601.000000      4601.000000
mean        0.016976        0.269071        0.075811        0.044238
std         0.109394        0.815672        0.245882        0.429342
min         0.000000        0.000000        0.000000        0.000000
25%         0.000000        0.000000        0.000000        0.000000
50%         0.000000        0.000000        0.000000        0.000000
75%         0.000000        0.315000        0.052000        0.000000
max         4.081000        32.478000        6.003000        19.829000

      capital_run_length_average  capital_run_length_longest  \
count      4601.000000      4601.000000
mean        5.191515      52.172789
std        31.729449      194.891310
min         1.000000        1.000000
25%         1.588000        6.000000
50%         2.276000      15.000000

```

75%	3.706000	43.000000
max	1102.500000	9989.000000

	capital_run_length_total	class
count	4601.000000	4601.000000
mean	283.289285	0.394045
std	606.347851	0.488698
min	1.000000	0.000000
25%	35.000000	0.000000
50%	95.000000	0.000000
75%	266.000000	1.000000
max	15841.000000	1.000000

[8 rows x 58 columns]

[4]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4601 entries, 0 to 4600
Data columns (total 58 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   word_freq_make                        4601 non-null   float64
1   word_freq_address                    4601 non-null   float64
2   word_freq_all                        4601 non-null   float64
3   word_freq_3d                        4601 non-null   float64
4   word_freq_our                        4601 non-null   float64
5   word_freq_over                       4601 non-null   float64
6   word_freq_remove                     4601 non-null   float64
7   word_freq_internet                   4601 non-null   float64
8   word_freq_order                      4601 non-null   float64
9   word_freq_mail                       4601 non-null   float64
10  word_freq_receive                    4601 non-null   float64
11  word_freq_will                       4601 non-null   float64
12  word_freq_people                     4601 non-null   float64
13  word_freq_report                     4601 non-null   float64
14  word_freq_addresses                  4601 non-null   float64
15  word_freq_free                       4601 non-null   float64
16  word_freq_business                   4601 non-null   float64
17  word_freq_email                      4601 non-null   float64
18  word_freq_you                        4601 non-null   float64
19  word_freq_credit                     4601 non-null   float64
20  word_freq_your                       4601 non-null   float64
21  word_freq_font                       4601 non-null   float64
22  word_freq_000                       4601 non-null   float64
23  word_freq_money                      4601 non-null   float64
24  word_freq_hp                         4601 non-null   float64
25  word_freq_hpl                        4601 non-null   float64
```

```

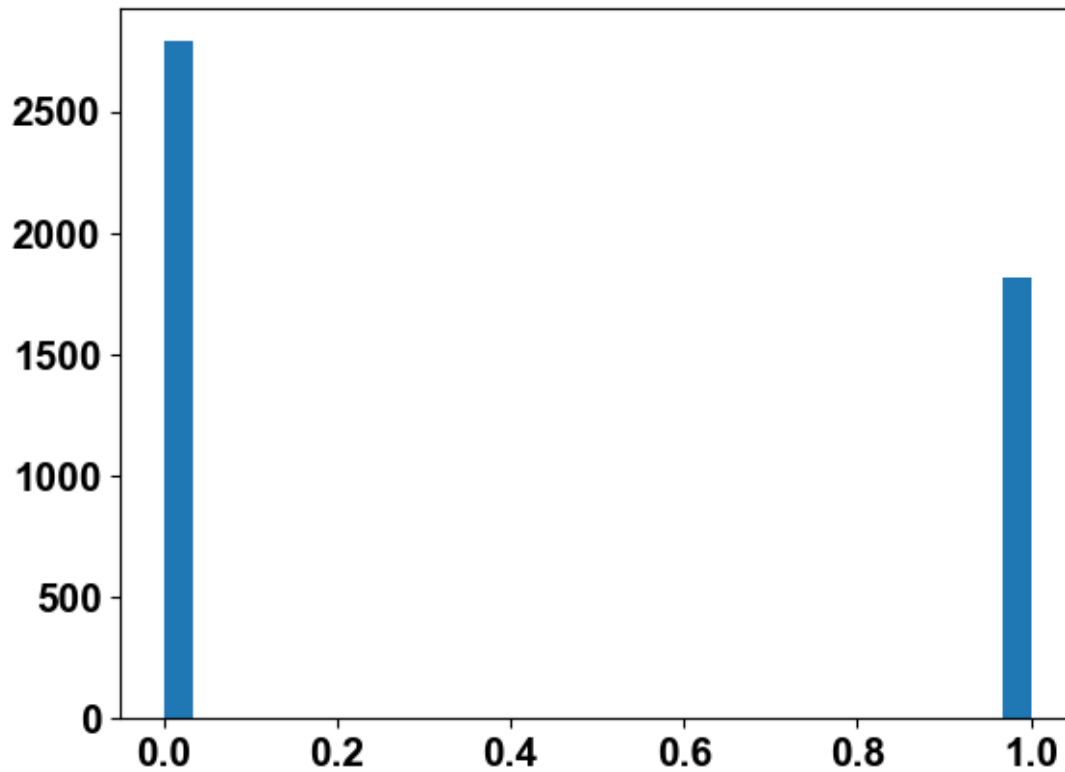
26 word_freq_george      4601 non-null float64
27 word_freq_650         4601 non-null float64
28 word_freq_lab         4601 non-null float64
29 word_freq_labs        4601 non-null float64
30 word_freq_telnet      4601 non-null float64
31 word_freq_857         4601 non-null float64
32 word_freq_data        4601 non-null float64
33 word_freq_415         4601 non-null float64
34 word_freq_85          4601 non-null float64
35 word_freq_technology   4601 non-null float64
36 word_freq_1999        4601 non-null float64
37 word_freq_parts       4601 non-null float64
38 word_freq_pm          4601 non-null float64
39 word_freq_direct      4601 non-null float64
40 word_freq_cs          4601 non-null float64
41 word_freq_meeting     4601 non-null float64
42 word_freq_original    4601 non-null float64
43 word_freq_project     4601 non-null float64
44 word_freq_re          4601 non-null float64
45 word_freq_edu         4601 non-null float64
46 word_freq_table       4601 non-null float64
47 word_freq_conference  4601 non-null float64
48 char_freq_%3B         4601 non-null float64
49 char_freq_%28         4601 non-null float64
50 char_freq_%5B         4601 non-null float64
51 char_freq_%21         4601 non-null float64
52 char_freq_%24         4601 non-null float64
53 char_freq_%23         4601 non-null float64
54 capital_run_length_average 4601 non-null float64
55 capital_run_length_longest 4601 non-null int64
56 capital_run_length_total 4601 non-null int64
57 class                 4601 non-null int64
dtypes: float64(55), int64(3)
memory usage: 2.0 MB

```

```

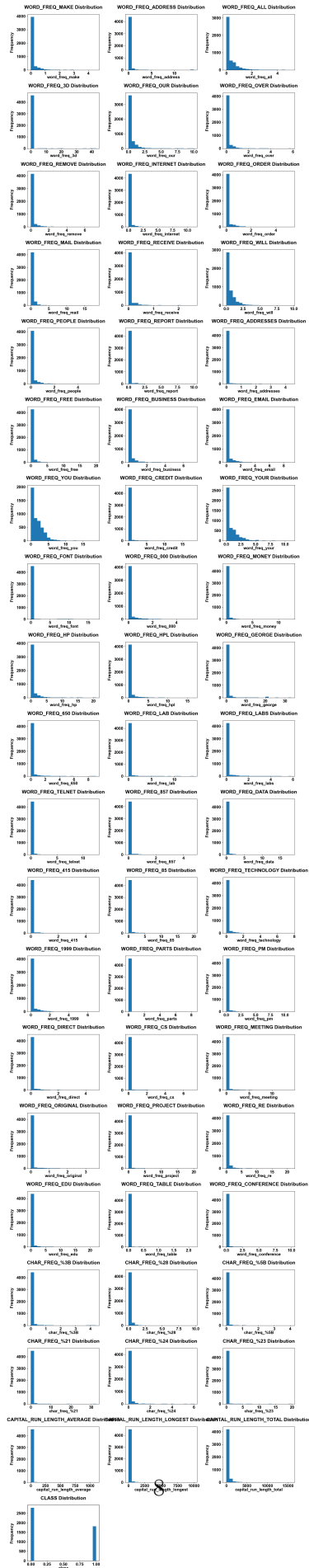
[24]: # isualize class distribution and feature behavior
plt.hist(df["class"],bins=30)
plt.savefig("class_distribution.png", dpi=300, bbox_inches="tight")

```



Histogram

```
[13]: bxwidth=1
rows=math.ceil(len(df.columns)/3)
fig,axes=plt.subplots(rows,3,figsize=(15,4*rows))
axes=axes.flatten()
columns=df.columns
for i,(ax,col) in enumerate(zip(axes,columns)):
    ax.hist(df[col],bins=20)
    ax.set_title(f"{col.upper()} Distribution",pad=20)
    ax.set_xlabel(col,labelpad=0)
    ax.set_ylabel("Frequency",labelpad=10)
for spine in ax.spines.values():
    spine.set_linewidth(bxwidth)
for j in range(i+1,len(axes)):
    fig.delaxes(axes[j])
plt.subplots_adjust(hspace=1.5,wspace=1.3)
plt.tight_layout()
plt.savefig("histogram.png", dpi=300, bbox_inches="tight")
plt.show()
```



Train-Test Split

```
[19]: X=df.iloc[:, :-1]
      y=df.iloc[:, -1]
      X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
      ↪2,stratify=y,random_state=42)
      print(X_train,X_test,y_train,y_test)
```

	word_freq_make	word_freq_address	word_freq_all	word_freq_3d	\
2940	0.05	0.00	0.45	0.0	
1303	0.17	0.26	1.21	0.0	
3468	0.00	0.00	0.00	0.0	
3181	0.00	0.00	0.00	0.0	
794	0.00	0.56	0.00	0.0	
...	
1861	0.00	0.00	4.00	0.0	
2366	0.00	0.00	0.00	0.0	
330	0.00	0.00	1.53	0.0	
536	0.00	0.00	0.00	0.0	
3114	0.00	0.00	0.00	0.0	

	word_freq_our	word_freq_over	word_freq_remove	word_freq_internet	\
2940	0.15	0.1	0.00	0.00	
1303	0.43	0.6	0.43	0.26	
3468	0.00	0.0	0.00	0.00	
3181	0.00	0.0	0.00	0.00	
794	0.56	0.0	0.00	0.00	
...	
1861	0.00	0.0	0.00	0.00	
2366	4.16	0.0	0.00	0.00	
330	0.00	0.0	0.00	0.00	
536	0.00	0.0	0.00	0.00	
3114	0.00	0.0	0.00	0.00	

	word_freq_order	word_freq_mail	...	word_freq_conference	\
2940	0.55	0.00	...	0.0	
1303	0.69	0.52	...	0.0	
3468	0.00	0.00	...	0.0	
3181	0.00	0.00	...	0.0	
794	1.01	0.56	...	0.0	
...	
1861	0.00	0.00	...	0.0	
2366	0.00	0.00	...	0.0	
330	0.00	0.00	...	0.0	
536	0.00	0.00	...	0.0	

3114	0.00	0.00	...	0.0
------	------	------	-----	-----

	char_freq_%3B	char_freq_%28	char_freq_%5B	char_freq_%21	\
2940	0.203	0.195	0.05	0.000	
1303	0.000	0.108	0.00	0.271	
3468	0.000	0.000	0.00	0.153	
3181	0.000	0.000	0.00	0.000	
794	0.000	0.186	0.00	0.056	
...	
1861	0.000	0.000	0.00	0.613	
2366	0.000	0.689	0.00	0.689	
330	0.000	0.000	0.00	1.434	
536	0.000	0.407	0.00	0.203	
3114	0.000	0.484	0.00	0.484	

	char_freq_%24	char_freq_%23	capital_run_length_average	\
2940	0.014	0.000	2.880	
1303	0.243	0.013	6.395	
3468	0.000	0.000	1.933	
3181	0.000	0.000	4.333	
794	0.056	0.000	2.153	
...	
1861	0.000	0.000	1.000	
2366	0.000	0.000	1.300	
330	0.000	0.000	7.055	
536	0.610	0.000	4.133	
3114	0.000	0.000	2.500	

	capital_run_length_longest	capital_run_length_total
2940	45	1080
1303	583	1375
3468	7	58
3181	20	26
794	53	532
...
1861	1	14
2366	4	13
330	75	127
536	17	62
3114	15	65

[3680 rows x 57 columns]		word_freq_make	word_freq_address	word_freq_all
word_freq_3d	\			
1472	0.00	0.00	0.00	0.0
258	0.00	0.00	0.33	0.0
3564	0.00	0.00	0.00	0.0
65	0.66	0.00	0.66	0.0
4303	0.00	0.00	0.00	0.0

...
1405	0.00	0.00	0.35	0.0
2312	0.00	2.59	1.29	0.0
2804	0.00	0.00	0.00	0.0
2047	0.00	0.00	0.00	0.0
2597	0.00	0.00	0.00	0.0

	word_freq_our	word_freq_over	word_freq_remove	word_freq_internet	\
1472	0.00	0.00	0.00	0.00	
258	0.99	0.99	0.33	0.33	
3564	0.00	0.00	0.00	0.00	
65	0.00	0.00	0.00	0.00	
4303	0.00	0.00	0.00	0.00	
...	
1405	0.00	0.70	0.35	0.35	
2312	1.29	0.00	0.00	0.00	
2804	0.00	0.00	0.00	0.00	
2047	0.34	0.00	0.00	0.00	
2597	0.00	0.00	0.00	0.00	

	word_freq_order	word_freq_mail	...	word_freq_conference	\
1472	0.0	0.00	...	0.00	
258	0.0	0.00	...	0.00	
3564	0.0	0.00	...	0.00	
65	0.0	0.66	...	0.00	
4303	0.0	2.77	...	0.00	
...	
1405	0.0	0.00	...	0.00	
2312	0.0	0.00	...	0.00	
2804	0.0	0.00	...	0.00	
2047	0.0	0.00	...	0.34	
2597	0.0	0.00	...	0.00	

	char_freq_%3B	char_freq_%28	char_freq_%5B	char_freq_%21	\
1472	0.144	0.000	0.000	3.907	
258	0.000	0.108	0.000	0.000	
3564	0.000	0.000	0.000	0.000	
65	0.000	0.000	0.000	2.205	
4303	0.000	0.000	0.000	0.438	
...	
1405	0.000	0.061	0.000	0.061	
2312	0.000	0.000	0.000	0.000	
2804	0.000	0.000	0.000	0.000	
2047	0.088	0.132	0.000	0.000	
2597	0.142	0.000	0.142	0.000	

	char_freq_%24	char_freq_%23	capital_run_length_average	\
1472	0.000	0.000	13.928	

258	0.162	0.054	2.195
3564	0.000	0.000	1.214
65	0.000	0.000	3.184
4303	0.000	0.000	1.214
...
1405	0.000	0.122	2.302
2312	0.000	0.000	1.000
2804	0.000	0.000	2.000
2047	0.000	0.000	1.250
2597	0.000	0.000	1.717

	capital_run_length_longest	capital_run_length_total
1472	70	195
258	50	202
3564	4	17
65	34	121
4303	3	17
...
1405	21	99
2312	1	13
2804	4	6
2047	7	85
2597	12	67

```
[921 rows x 57 columns] 2940    0
1303    1
3468    0
3181    0
794     1
..
1861    0
2366    0
330     1
536     1
3114    0
Name: class, Length: 3680, dtype: int64 1472    1
258     1
3564    0
65      1
4303    0
..
1405    1
2312    0
2804    0
2047    0
2597    0
Name: class, Length: 921, dtype: int64
```

Z-score or Standard Scaling

```
[21]: scaler=StandardScaler()
      X_train_scaled=scaler.fit_transform(X_train)
      X_test_scaled=scaler.transform(X_test)
      print(X_train,X_test,y_train,y_test)
```

	word_freq_make	word_freq_address	word_freq_all	word_freq_3d	\
2940	0.05	0.00	0.45	0.0	
1303	0.17	0.26	1.21	0.0	
3468	0.00	0.00	0.00	0.0	
3181	0.00	0.00	0.00	0.0	
794	0.00	0.56	0.00	0.0	
...	
1861	0.00	0.00	4.00	0.0	
2366	0.00	0.00	0.00	0.0	
330	0.00	0.00	1.53	0.0	
536	0.00	0.00	0.00	0.0	
3114	0.00	0.00	0.00	0.0	

	word_freq_our	word_freq_over	word_freq_remove	word_freq_internet	\
2940	0.15	0.1	0.00	0.00	
1303	0.43	0.6	0.43	0.26	
3468	0.00	0.0	0.00	0.00	
3181	0.00	0.0	0.00	0.00	
794	0.56	0.0	0.00	0.00	
...	
1861	0.00	0.0	0.00	0.00	
2366	4.16	0.0	0.00	0.00	
330	0.00	0.0	0.00	0.00	
536	0.00	0.0	0.00	0.00	
3114	0.00	0.0	0.00	0.00	

	word_freq_order	word_freq_mail	...	word_freq_conference	\
2940	0.55	0.00	...	0.0	
1303	0.69	0.52	...	0.0	
3468	0.00	0.00	...	0.0	
3181	0.00	0.00	...	0.0	
794	1.01	0.56	...	0.0	
...	
1861	0.00	0.00	...	0.0	
2366	0.00	0.00	...	0.0	
330	0.00	0.00	...	0.0	
536	0.00	0.00	...	0.0	
3114	0.00	0.00	...	0.0	

	char_freq_%3B	char_freq_%28	char_freq_%5B	char_freq_%21	\
2940	0.203	0.195	0.05	0.000	

1303	0.000	0.108	0.00	0.271
3468	0.000	0.000	0.00	0.153
3181	0.000	0.000	0.00	0.000
794	0.000	0.186	0.00	0.056
...
1861	0.000	0.000	0.00	0.613
2366	0.000	0.689	0.00	0.689
330	0.000	0.000	0.00	1.434
536	0.000	0.407	0.00	0.203
3114	0.000	0.484	0.00	0.484

	char_freq_%24	char_freq_%23	capital_run_length_average	\
2940	0.014	0.000		2.880
1303	0.243	0.013		6.395
3468	0.000	0.000		1.933
3181	0.000	0.000		4.333
794	0.056	0.000		2.153
...
1861	0.000	0.000		1.000
2366	0.000	0.000		1.300
330	0.000	0.000		7.055
536	0.610	0.000		4.133
3114	0.000	0.000		2.500

	capital_run_length_longest	capital_run_length_total
2940	45	1080
1303	583	1375
3468	7	58
3181	20	26
794	53	532
...
1861	1	14
2366	4	13
330	75	127
536	17	62
3114	15	65

[3680 rows x 57 columns]		word_freq_make	word_freq_address	word_freq_all
word_freq_3d \				
1472	0.00	0.00	0.00	0.0
258	0.00	0.00	0.33	0.0
3564	0.00	0.00	0.00	0.0
65	0.66	0.00	0.66	0.0
4303	0.00	0.00	0.00	0.0
...
1405	0.00	0.00	0.35	0.0
2312	0.00	2.59	1.29	0.0
2804	0.00	0.00	0.00	0.0

2047	0.00	0.00	0.00	0.0
2597	0.00	0.00	0.00	0.0

	word_freq_our	word_freq_over	word_freq_remove	word_freq_internet	\
1472	0.00	0.00	0.00	0.00	
258	0.99	0.99	0.33	0.33	
3564	0.00	0.00	0.00	0.00	
65	0.00	0.00	0.00	0.00	
4303	0.00	0.00	0.00	0.00	
...	
1405	0.00	0.70	0.35	0.35	
2312	1.29	0.00	0.00	0.00	
2804	0.00	0.00	0.00	0.00	
2047	0.34	0.00	0.00	0.00	
2597	0.00	0.00	0.00	0.00	

	word_freq_order	word_freq_mail	...	word_freq_conference	\
1472	0.0	0.00	...	0.00	
258	0.0	0.00	...	0.00	
3564	0.0	0.00	...	0.00	
65	0.0	0.66	...	0.00	
4303	0.0	2.77	...	0.00	
...	
1405	0.0	0.00	...	0.00	
2312	0.0	0.00	...	0.00	
2804	0.0	0.00	...	0.00	
2047	0.0	0.00	...	0.34	
2597	0.0	0.00	...	0.00	

	char_freq_%3B	char_freq_%28	char_freq_%5B	char_freq_%21	\
1472	0.144	0.000	0.000	3.907	
258	0.000	0.108	0.000	0.000	
3564	0.000	0.000	0.000	0.000	
65	0.000	0.000	0.000	2.205	
4303	0.000	0.000	0.000	0.438	
...	
1405	0.000	0.061	0.000	0.061	
2312	0.000	0.000	0.000	0.000	
2804	0.000	0.000	0.000	0.000	
2047	0.088	0.132	0.000	0.000	
2597	0.142	0.000	0.142	0.000	

	char_freq_%24	char_freq_%23	capital_run_length_average	\
1472	0.000	0.000	13.928	
258	0.162	0.054	2.195	
3564	0.000	0.000	1.214	
65	0.000	0.000	3.184	
4303	0.000	0.000	1.214	

...
1405	0.000	0.122	2.302
2312	0.000	0.000	1.000
2804	0.000	0.000	2.000
2047	0.000	0.000	1.250
2597	0.000	0.000	1.717

	capital_run_length_longest	capital_run_length_total
1472	70	195
258	50	202
3564	4	17
65	34	121
4303	3	17
...
1405	21	99
2312	1	13
2804	4	6
2047	7	85
2597	12	67

[921 rows x 57 columns] 2940 0

1303	1
3468	0
3181	0
794	1
..	
1861	0
2366	0
330	1
536	1
3114	0
Name: class, Length: 3680, dtype: int64	1472 1
258	1
3564	0
65	1
4303	0
..	
1405	1
2312	0
2804	0
2047	0
2597	0

Name: class, Length: 921, dtype: int64

Naive Bayes GaussianNB

```
[27]: start=time.time()
      gnb=GaussianNB()
```



```
gnb.fit(X_train_scaled,y_train)
ttgnb=time.time()-start
y_pred=gnb.predict(X_test_scaled)
print("The training time for Gaussian Naive Bayes is: ",ttgnb)
```

The training time for Gaussian Naive Bayes is: 0.00466465950012207

```
[39]: start=time.time()
y_pred=gnb.predict(X_test_scaled)
ptgnb=time.time()-start
print("The Prediction time for Gaussian Naive Bayes is: ",ptgnb)
```

The Prediction time for Gaussian Naive Bayes is: 0.0009808540344238281

Accuracy

```
[30]: accuracy_score(y_test,y_pred)
```

```
[30]: 0.8327904451682954
```

Precision

```
[31]: precision_score(y_test,y_pred)
```

```
[31]: 0.7145790554414785
```

Recall

```
[32]: recall_score(y_test,y_pred)
```

```
[32]: 0.9586776859504132
```

F1 Score

```
[33]: f1_score(y_test,y_pred)
```

```
[33]: 0.8188235294117647
```

```
[34]: cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[419 139]
 [ 15 348]]
```

Specificity and False Positive Rate

```
[36]: TN, FP, FN, TP = cm.ravel()
specificity = TN / (TN + FP)
false_positive_rate = FP / (FP + TN)

print("Specificity:", specificity)
print("False Positive Rate:", false_positive_rate)
```

Specificity: 0.7508960573476703
False Positive Rate: 0.24910394265232974

```
[37]: print("Overall Report of model \n\n",classification_report(y_test,y_pred))
```

Overall Report of model

	precision	recall	f1-score	support
0	0.97	0.75	0.84	558
1	0.71	0.96	0.82	363
accuracy			0.83	921
macro avg	0.84	0.85	0.83	921
weighted avg	0.87	0.83	0.83	921

MultinomialNB

```
[40]: start=time.time()
mnf=MultinomialNB()
mnf.fit(X_train,y_train)
ttmnf=time.time()-start

print("The training time for Multinomial Naive Bayes is: ",ttmnf)
```

The training time for Multinomial Naive Bayes is: 0.009273767471313477

```
[41]: start=time.time()
y_pred=mnf.predict(X_test)
ptmnf=time.time()-start
print("The Prediction time for Multinomial Naive Bayes is: ",ptmnf)
```

The Prediction time for Multinomial Naive Bayes is: 0.009157180786132812

Accuracy

```
[42]: accuracy_score(y_test,y_pred)
```

```
[42]: 0.7763300760043431
```

Precision Score

```
[43]: precision_score(y_test,y_pred)
```

```
[43]: 0.7198879551820728
```

Recall-score

```
[44]: recall_score(y_test,y_pred)
```

```
[44]: 0.7079889807162535
```

F1-score

```
[45]: f1_score(y_test,y_pred)
```

```
[45]: 0.7138888888888889
```

```
[46]: print("Confusion matrix is \n",confusion_matrix(y_test,y_pred))
```

Confusion matrix is

```
[[458 100]
 [106 257]]
```

```
[48]: TN, FP, FN, TP = cm.ravel()
specificity = TN / (TN + FP)
false_positive_rate = FP / (FP + TN)

print("Specificity:", specificity)
print("False Positive Rate:", false_positive_rate)
```

Specificity: 0.7508960573476703

False Positive Rate: 0.24910394265232974

```
[47]: print("Overall Report of model \n\n",classification_report(y_test,y_pred))
```

Overall Report of model

	precision	recall	f1-score	support
0	0.81	0.82	0.82	558
1	0.72	0.71	0.71	363
accuracy			0.78	921
macro avg	0.77	0.76	0.77	921
weighted avg	0.78	0.78	0.78	921

BernoulliNB

```
[49]: start=time.time()
bnb=BernoulliNB()
bnb.fit(X_train,y_train)
ttbnb=time.time()-start
print("The training time for Bernoulli Naive Bayes is: ",ttbnb)
```

The training time for Bernoulli Naive Bayes is: 0.02569127082824707

```
[50]: start=time.time()
y_pred=bnb.predict(X_test)
```

```
ptbnb=time.time()-start
```

```
print("The prediction time for Bernoulli Naive Bayes is: ",ptbnb)
```

The prediction time for Bernoulli Naive Bayes is: 0.003880739212036133

Accuracy

```
[51]: accuracy_score(y_test,y_pred)
```

```
[51]: 0.8762214983713354
```

Precision

```
[52]: precision_score(y_test,y_pred)
```

```
[52]: 0.8716417910447761
```

Recall Score

```
[53]: recall_score(y_test,y_pred)
```

```
[53]: 0.8044077134986226
```

F1-score

```
[54]: f1_score(y_test,y_pred)
```

```
[54]: 0.836676217765043
```

```
[56]: print("Confusion matrix is \n",confusion_matrix(y_test,y_pred))
```

Confusion matrix is

```
[[515  43]
```

```
 [ 71 292]]
```

```
[57]: TN, FP, FN, TP = cm.ravel()
specificity = TN / (TN + FP)
false_positive_rate = FP / (FP + TN)

print("Specificity:", specificity)
print("False Positive Rate:", false_positive_rate)
```

Specificity: 0.7508960573476703

False Positive Rate: 0.24910394265232974

```
[58]: print("Overall Report of model \n\n",classification_report(y_test,y_pred))
```

Overall Report of model

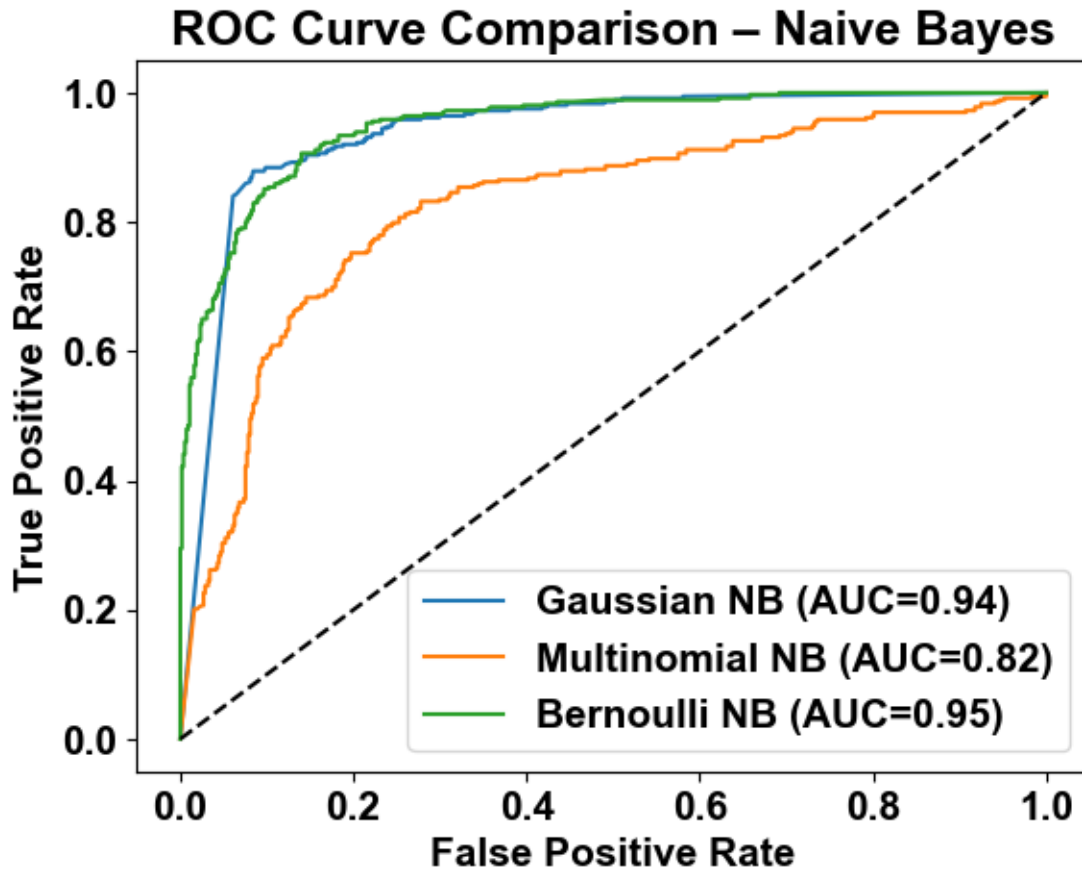
	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.88	0.92	0.90	558
1	0.87	0.80	0.84	363
accuracy			0.88	921
macro avg	0.88	0.86	0.87	921
weighted avg	0.88	0.88	0.88	921

ROC curve

```
[59]: y_prob_gnb=gnb.predict_proba(X_test_scaled)[: ,1]
      y_prob_mnb=mnb.predict_proba(X_test)[: ,1]
      y_prob_bnb=bnb.predict_proba(X_test)[: ,1]
```

```
[60]: fpr_gnb,tpr_gnb,_=roc_curve(y_test,y_prob_gnb)
      fpr_mnb,tpr_mnb,_=roc_curve(y_test,y_prob_mnb)
      fpr_bnb,tpr_bnb,_=roc_curve(y_test,y_prob_bnb)
      auc_gnb=auc(fpr_gnb,tpr_gnb)
      auc_mnb=auc(fpr_mnb,tpr_mnb)
      auc_bnb=auc(fpr_bnb,tpr_bnb)
      plt.plot(fpr_gnb,tpr_gnb,label=f'Gaussian NB (AUC={auc_gnb:.2f})')
      plt.plot(fpr_mnb,tpr_mnb,label=f'Multinomial NB (AUC={auc_mnb:.2f})')
      plt.plot(fpr_bnb,tpr_bnb,label=f'Bernoulli NB (AUC={auc_bnb:.2f})')
      plt.plot([0,1],[0,1], 'k--')
      plt.xlabel("False Positive Rate")
      plt.ylabel("True Positive Rate")
      plt.title("ROC Curve Comparison - Naive Bayes")
      plt.legend()
      plt.savefig("roc_curve.png", dpi=300, bbox_inches="tight")
      plt.show()
```



K-Nearest Neighbour

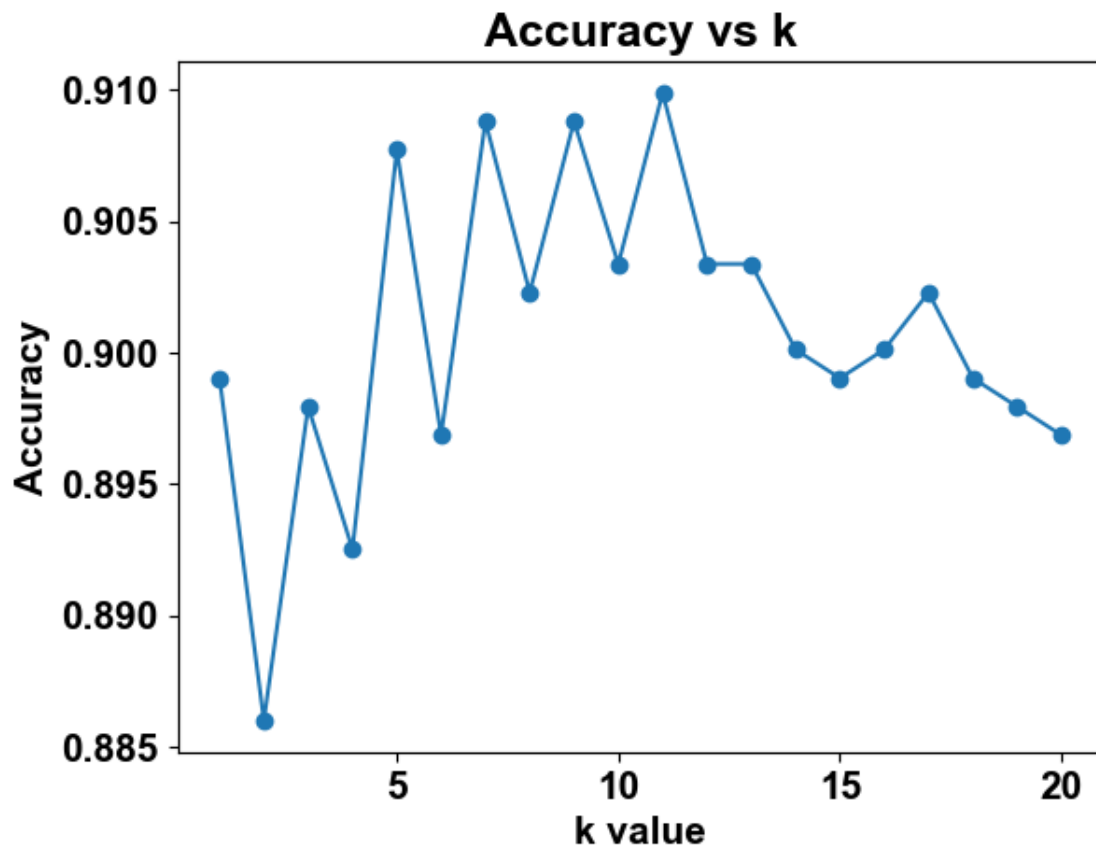
Basic Model

```
[61]: knn = KNeighborsClassifier()
      knn.fit(X_train_scaled, y_train)
      y_pred_knn = knn.predict(X_test_scaled)
```

Statistical significance test Anova-N

```
[76]: k_values = range(1, 21)
      accuracies = []
      for k in k_values:
          knn = KNeighborsClassifier(n_neighbors=k)
          knn.fit(X_train_scaled, y_train)
          accuracies.append(knn.score(X_test_scaled, y_test))
      plt.plot(k_values, accuracies, marker='o')
      plt.xlabel('k value')
      plt.ylabel('Accuracy')
      plt.title('Accuracy vs k')
```

```
plt.savefig("accuracy_vs_k.png", dpi=300, bbox_inches="tight")
plt.show()
```



Stratified K-Fold

```
[77]: skf=StratifiedKFold(n_splits=5,shuffle=True,random_state=42)
cv_scores_base=cross_val_score(
    knn,
    X_train_scaled,
    y_train,
    cv=skf,
    scoring='accuracy'
)
print("Base KNN CV Accuracy:",cv_scores_base.mean())
```

Base KNN CV Accuracy: 0.8932065217391303

Grid Search

```
[78]: param_grid={
    'n_neighbors':list(range(1,31,2)),
```

```

        'weights':['uniform','distance'],
        'metric':['euclidean','manhattan']
    }
    grid=GridSearchCV(
        knn,
        param_grid,
        cv=skf,
        scoring='accuracy',
        n_jobs=-1
    )
    grid.fit(X_train_scaled,y_train)
    print("Grid Best Params:",grid.best_params_)
    print("Grid Best CV Accuracy:",grid.best_score_)

```

Grid Best Params: {'metric': 'manhattan', 'n_neighbors': 9, 'weights': 'distance'}

Grid Best CV Accuracy: 0.9252717391304348

Randomized Search

```

[79]: from scipy.stats import randint
    param_dist={
        'n_neighbors':randint(1,30),
        'weights':['uniform','distance'],
        'metric':['euclidean','manhattan']
    }
    rand=RandomizedSearchCV(
        knn,
        param_distributions=param_dist,
        n_iter=15,
        cv=skf,
        scoring='accuracy',
        random_state=42,
        n_jobs=-1
    )
    rand.fit(X_train_scaled,y_train)
    print("Random Best Params:",rand.best_params_)
    print("Random Best CV Accuracy:",rand.best_score_)

```

Random Best Params: {'metric': 'manhattan', 'n_neighbors': 6, 'weights': 'distance'}

Random Best CV Accuracy: 0.9241847826086957

Final KNN Model

```

[80]: best_params=grid.best_params_
    knn_final=KNeighborsClassifier(
        n_neighbors=best_params['n_neighbors'],
        weights=best_params['weights'],

```



```

        metric=best_params['metric']
    )
    knn_final.fit(X_train_scaled,y_train)
    y_pred_final=knn_final.predict(X_test_scaled)

```

Metrics

```

[81]: from sklearn.metrics import confusion_matrix,roc_curve, auc
def compute_metrics(y_true,y_pred):
    cm=confusion_matrix(y_true,y_pred)
    tn,fp,fn,tp=cm.ravel()
    accuracy=(tp+tn)/(tp+tn+fp+fn)
    precision=tp/(tp+fp)
    recall=tp/(tp+fn)
    f1=2*precision*recall/(precision+recall)
    specificity=tn/(tn+fp)
    fpr=fp/(fp+tn)
    return accuracy,precision,recall,f1,specificity,fpr,cm

```

```

[82]: start=time.time()
knn_final.fit(X_train_scaled,y_train)
train_time=time.time()-start

start=time.time()
y_pred_knn=knn_final.predict(X_test_scaled)
pred_time=time.time()-start
acc,prec,rec,f1,spec,fpr,cm=compute_metrics(y_test,y_pred_knn)
print("Final KNN Metrics")
print("Accuracy:",acc)
print("Precision:",prec)
print("Recall:",rec)
print("F1 Score:",f1)
print("Specificity:",spec)
print("False Positive Rate:",fpr)
print("Training Time:",train_time)
print("Prediction Time:",pred_time)

```

Final KNN Metrics

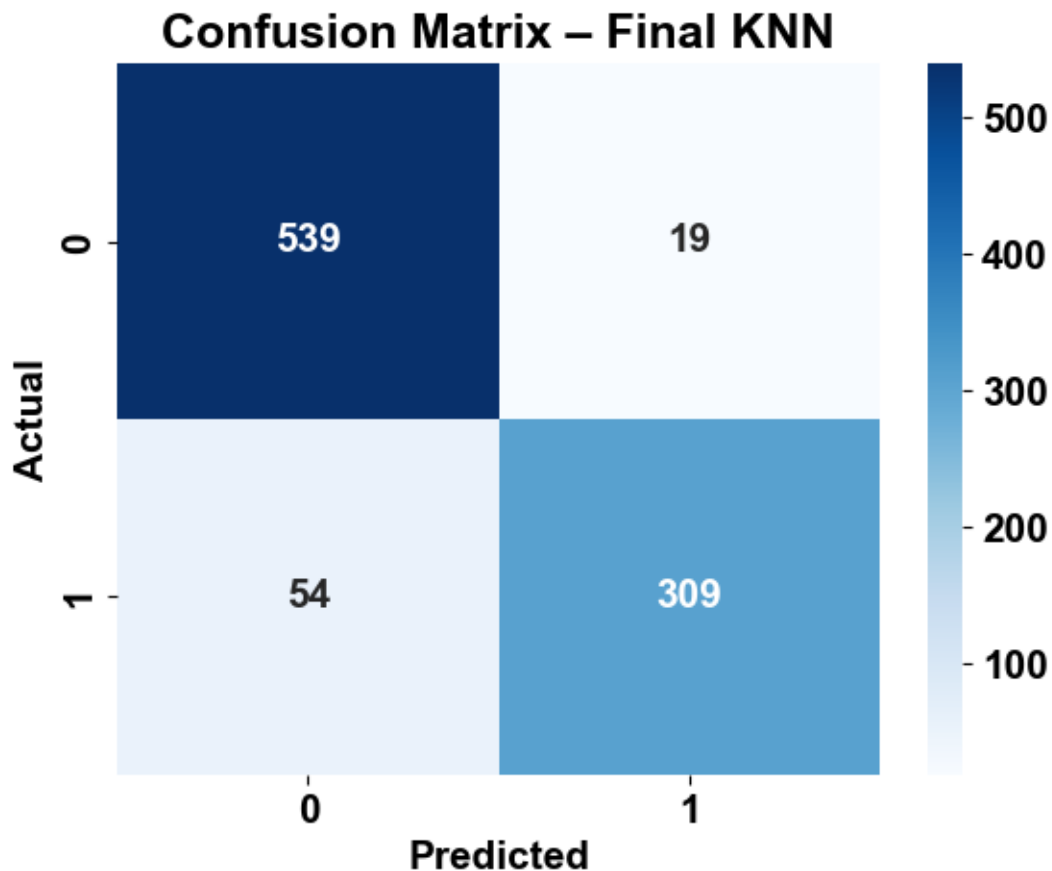
```

Accuracy: 0.9207383279044516
Precision: 0.9420731707317073
Recall: 0.8512396694214877
F1 Score: 0.894356005788712
Specificity: 0.9659498207885304
False Positive Rate: 0.034050179211469536
Training Time: 0.004589557647705078
Prediction Time: 0.09273862838745117

```

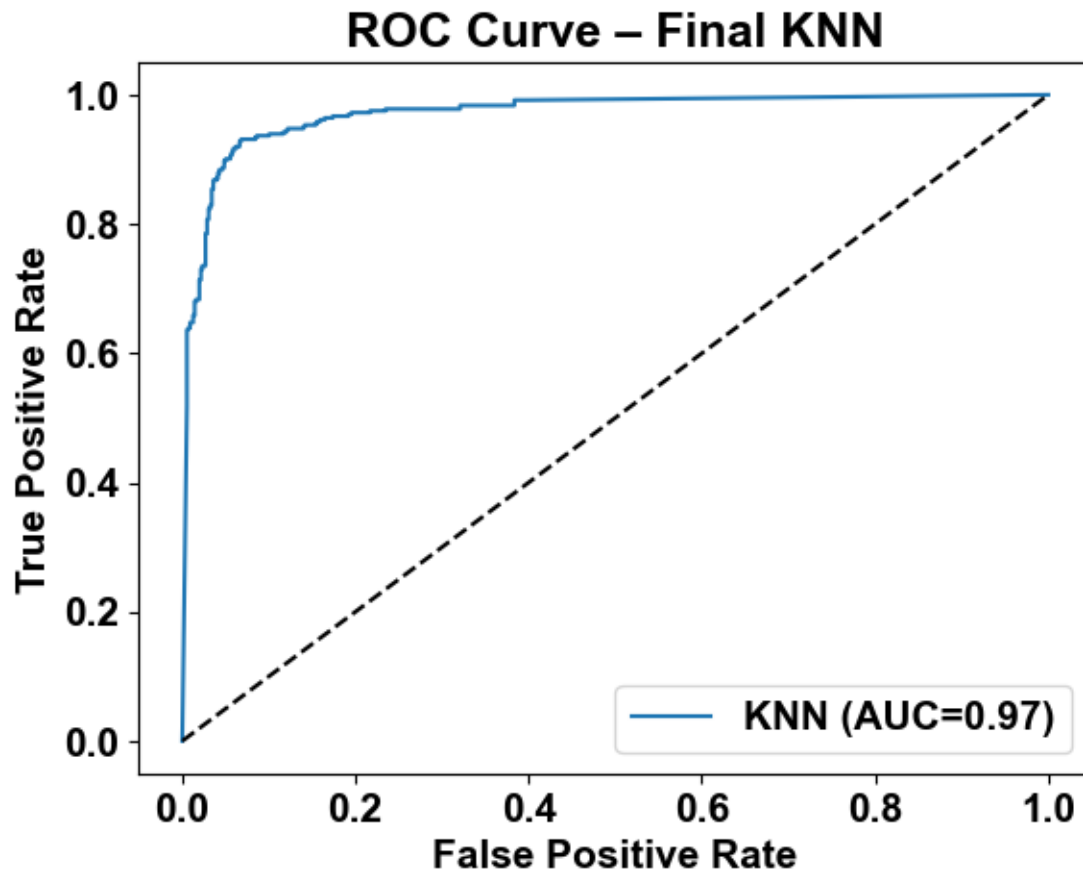
Confusion Matrix

```
[83]: sns.heatmap(cm,annot=True,fmt='d',cmap='Blues')
plt.title("Confusion Matrix - Final KNN")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



ROC Curve for KNN

```
[85]: y_prob_knn=knn_final.predict_proba(X_test_scaled)[:,-1]
fpr_knn,tpr_knn,_=roc_curve(y_test,y_prob_knn)
auc_knn=auc(fpr_knn,tpr_knn)
plt.plot(fpr_knn,tpr_knn,label=f'KNN (AUC={auc_knn:.2f})')
plt.plot([0,1],[0,1],'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - Final KNN")
plt.legend()
plt.savefig("roc_curve_finalKNN.png", dpi=300, bbox_inches="tight")
plt.show()
```



```
[86]: best_params=grid.best_params_  
       optimal_k=best_params['n_neighbors']
```

Evaluating all models using multiple metrics

KDTree

```
[87]: start=time.time()  
       knn_kd=KNeighborsClassifier(  
           n_neighbors=optimal_k,  
           weights=best_params['weights'],  
           metric=best_params['metric'],  
           algorithm='kd_tree'  
       )  
       knn_kd.fit(X_train_scaled,y_train)  
       train_time_kd=time.time()-start  
       start=time.time()  
       y_pred_kd=knn_kd.predict(X_test_scaled)  
       pred_time_kd=time.time()-start
```

```
[88]: acc_kd,prec_kd,rec_kd,f1_kd,sp,fpr,cm=compute_metrics(y_test,y_pred_kd)
print("Final KDtree Metrics")
print("Accuracy:",acc_kd)
print("Precision:",prec_kd)
print("Recall:",rec_kd)
print("F1 Score:",f1_kd)
print("Specificity:",sp)
print("False Positive Rate:",fpr)
print("Training Time:",train_time)
print("Prediction Time:",pred_time)
```

Final KDtree Metrics
Accuracy: 0.9207383279044516
Precision: 0.9420731707317073
Recall: 0.8512396694214877
F1 Score: 0.894356005788712
Specificity: 0.9659498207885304
False Positive Rate: 0.034050179211469536
Training Time: 0.004589557647705078
Prediction Time: 0.09273862838745117

BallTree

```
[89]: start=time.time()
knn_bt=KNeighborsClassifier(
    n_neighbors=optimal_k,
    weights=best_params['weights'],
    metric=best_params['metric'],
    algorithm='ball_tree'
)
knn_bt.fit(X_train_scaled,y_train)
train_time_bt=time.time()-start
start=time.time()
y_pred_bt=knn_bt.predict(X_test_scaled)
pred_time_bt=time.time()-start
```

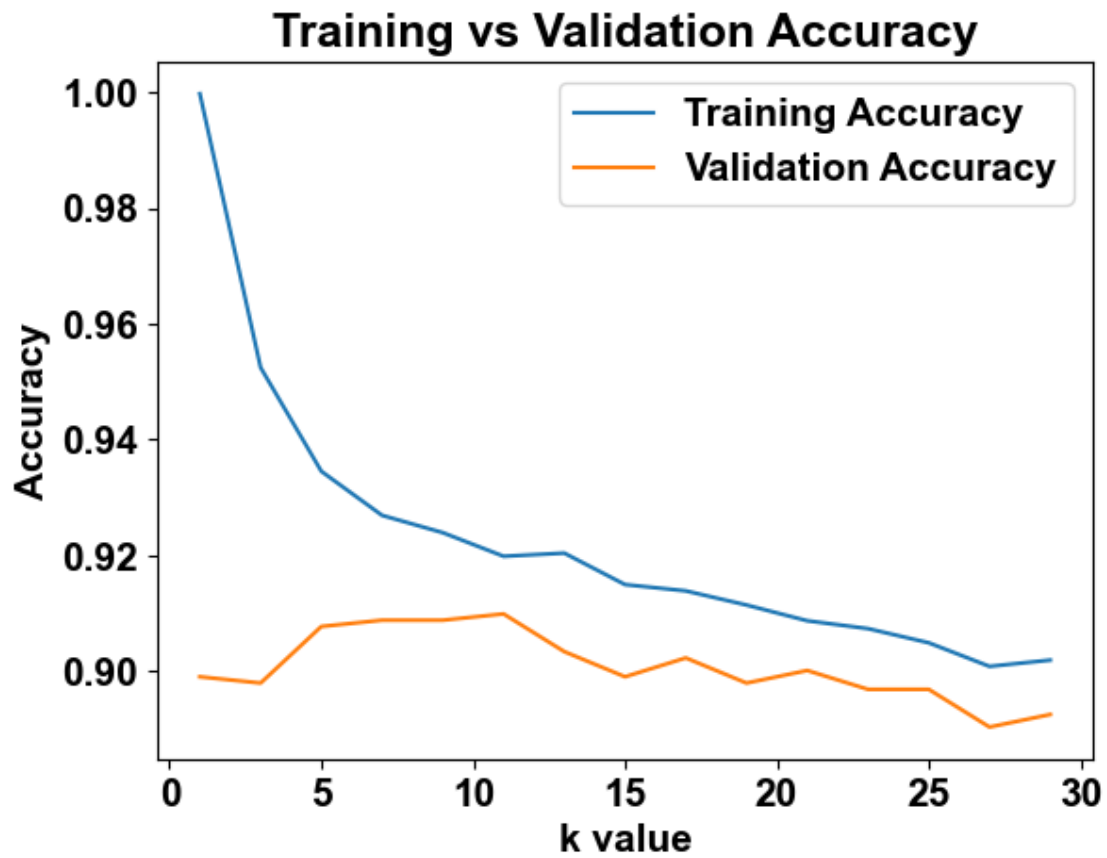
```
[90]: acc_bt,prec_bt,rec_bt,f1_bt,sp,fpr,cm=compute_metrics(y_test,y_pred_bt)
print("Final Balltree Metrics")
print("Accuracy:",acc_bt)
print("Precision:",prec_bt)
print("Recall:",rec_bt)
print("F1 Score:",f1_bt)
print("Specificity:",sp)
print("False Positive Rate:",fpr)
print("Training Time:",train_time)
print("Prediction Time:",pred_time)
```

Final Balltree Metrics
Accuracy: 0.9207383279044516

Precision: 0.9420731707317073
Recall: 0.8512396694214877
F1 Score: 0.894356005788712
Specificity: 0.9659498207885304
False Positive Rate: 0.034050179211469536
Training Time: 0.004589557647705078
Prediction Time: 0.09273862838745117

Training vs Validation

```
[92]: train_acc=[]  
      val_acc=[]  
      k_values=range(1,31,2)  
      for k in k_values:  
          knn=KNeighborsClassifier(n_neighbors=k)  
          knn.fit(X_train_scaled,y_train)  
          train_acc.append(knn.score(X_train_scaled,y_train))  
          val_acc.append(knn.score(X_test_scaled,y_test))  
      plt.plot(k_values,train_acc,label='Training Accuracy')  
      plt.plot(k_values,val_acc,label='Validation Accuracy')  
      plt.xlabel('k value')  
      plt.ylabel('Accuracy')  
      plt.title('Training vs Validation Accuracy')  
      plt.legend()  
      plt.savefig("training_vs_validation_accuracy.png", dpi=300, bbox_inches="tight")  
      plt.show()
```



Cross Validation Scores

```
[102]: gnb_scores=cross_val_score(  
        GaussianNB(),  
        X_train,  
        y_train,  
        cv=skf,  
        scoring='precision'  
    )
```

```
[103]: mnb_scores=cross_val_score(  
        MultinomialNB(),  
        X_train,  
        y_train,  
        cv=skf,  
        scoring='precision'  
    )
```

```
[104]: bnb_scores=cross_val_score(  
        BernoulliNB(),
```

```

X_train,
y_train,
cv=skf,
scoring='precision'
)

```

```

[105]: knn_kd_scores=cross_val_score(
        knn_kd,
        X_train_scaled,
        y_train,
        cv=skf,
        scoring='precision'
    )

```

```

[106]: knn_bt_scores=cross_val_score(
        knn_bt,
        X_train_scaled,
        y_train,
        cv=skf,
        scoring='precision'
    )

```

One way ANOVA Test

```

[107]: from scipy.stats import f_oneway
F_stat,p_value=f_oneway(
        gnb_scores,
        mnb_scores,
        bnb_scores,
        knn_kd_scores,
        knn_bt_scores
    )

print("F-statistic:",F_stat)
print("p-value:",p_value)

```

F-statistic: 147.4451411146714

p-value: 1.537483731179684e-14

Mean Accuracy to find the best model

```

[108]: print("Gaussian NB Mean precision:",gnb_scores.mean())
        print("Multinomial NB Mean precision:",mnb_scores.mean())
        print("Bernoulli NB Mean precision:",bnb_scores.mean())
        print("KNN KDTree Mean precision:",knn_kd_scores.mean())
        print("KNN BallTree Mean precision:",knn_bt_scores.mean())

```

Gaussian NB Mean precision: 0.7011869673414239

Multinomial NB Mean precision: 0.737146025168714

Bernoulli NB Mean precision: 0.8894670120013128
 KNN KDTree Mean precision: 0.948881300360718
 KNN BallTree Mean precision: 0.948881300360718

```
[109]: best_model=max(
    [
        ("Gaussian NB", gnb_scores.mean()),
        ("Multinomial NB", mnb_scores.mean()),
        ("Bernoulli NB", bnb_scores.mean()),
        ("KNN KDTree", knn_kd_scores.mean()),
        ("KNN BallTree", knn_bt_scores.mean())
    ],
    key=lambda x: x[1]
)

print("Best Model:", best_model)
```

Best Model: ('KNN KDTree', np.float64(0.948881300360718))

```
[ ]:
```

Naïve Bayes Performance Comparison

Metric	Gaussian NB	Multinomial NB	Bernoulli NB
Accuracy	0.8327	0.7763	0.8762
Precision	0.7145	0.7198	0.8716
Recall	0.9586	0.7079	0.8044
F1 Score	0.8188	0.7138	0.8366
Specificity	0.7508	0.7508	0.7508
Training Time (s)	0.0046	0.0092	0.0256

KNN Hyperparameter Tuning Results

Search Method	Best k	Best CV Accuracy	Best Parameters
Grid Search	9	0.9252	'metric': 'manhattan', 'weights': 'distance'
Randomized Search	6	0.9241	'metric': 'manhattan', 'weights': 'distance'

KNN Performance using Different Search Methods

Metric (KDTree)	Value
Optimal k	9
Accuracy	0.9207
Precision	0.9420
Recall	0.8512
F1 Score	0.8943
Training Time (s)	0.0056
Prediction Time (s)	0.0406

Metric (BallTree)	Value
Optimal k	9
Accuracy	0.9207
Precision	0.9420
Recall	0.8512
F1 Score	0.8943
Training Time (s)	0.0056
Prediction Time (s)	0.0406

KDTree vs BallTree Comparison

Criterion	KDTree	BallTree
Accuracy	0.9207	0.9207
Training Time (s)	0.0056	0.0056
Prediction Time (s)	0.0406	0.0406
Memory Usage	Low / Medium	Medium / High

Conclusion

Naïve Bayes provides fast and stable performance with high bias, whereas optimized KNN achieves better accuracy and generalization through careful hyperparameter tuning, with KDTree and BallTree improving computational efficiency.

References

- [Scikit-learn: Naïve Bayes](#)
- [Scikit-learn: KNN](#)
- [Scikit-learn: Hyperparameter Optimization](#)
- [Spambase Dataset](#)