SPAM OR HAM MESSAGE CLASSIFICATION BY USING MACHINE LEARNING ALGORITHMS

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INTRODUCTION :

The exponential growth of digital communication has led to an increase in the volume of spam messages, posing a significant challenge to effective communication. Spam messages not only clutter inboxes but also pose security risks and can lead to phishing attacks and malware

distribution. In response to this issue, the development of efficient spam filters has become crucial to distinguish legitimate messages (ham) from unwanted spam messages.

OBJECTIVES:

Develop a robust machine learning classifier capable of accurately distinguishing spam from ham messages. Enhance communication efficiency by filtering out spam messages, ensuring users receive only relevant messages. Minimize security risks associated with spam, such as phishing attacks and malware distribution.

Methodology:

1. **Data Collection**: Gather a diverse dataset containing labeled examples of spam and ham messages.
2. **Data Preprocessing**: Clean and transform the text data, removing stopwords and handling special characters.
3. **Feature Extraction**: Convert textual data into numerical features using techniques like Bag-of-Words or TF-IDF.
4. **Model Selection**: Experiment with various machine learning algorithms such as Naive Bayes, SVM, and Random Forests to identify the best-performing model.
5. **Model Training and Evaluation**: Train the selected model on preprocessed data and evaluate its performance using metrics like accuracy and F1-score.
6. **Hyperparameter Tuning**: Fine-tune the model's hyperparameters to optimize performance using techniques like GridSearchCV.
7. **Cross-Validation**: Perform cross-validation to assess the model's generalization performance across different data subsets.
8. **Deployment**: Deploy the trained classifier in a real-world environment to classify incoming messages in real-time.

PROBLEM STATEMENT

The SMS Spam Collection is a set of SMS tagged messages that have been collected for SMS Spam research. It contains one set of SMS messages in English of 5,574 messages, tagged acording being ham (legitimate) or spam.

The files contain one message per line. Each line is composed by two columns: type contains the label (ham or spam) and text contains the raw text.

```
#for checking our current working directory in which we working
import os
os.getcwd()
```

```
'C:\\Users\\admin\\Downloads'
```

IMPORTING LIBRARIES

```
# importing required library
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, classification_report
import warnings
warnings.filterwarnings('ignore')
```

1. READING THE DATA

```
# reading the csv file
df=pd.read_csv(r'sms_spam.csv')
df
```

```
      type                                               text
0      ham  Go until jurong point, crazy.. Available only ...
1      ham                      Ok lar... Joking wif u oni...
2     spam  Free entry in 2 a wkly comp to win FA Cup fina...
3      ham  U dun say so early hor... U c already then say...
4      ham  Nah I don't think he goes to usf, he lives aro...
...    ...                                                ...
5569  spam  This is the 2nd time we have tried 2 contact u...
5570   ham               Will ü b going to esplanade fr home?
5571   ham  Pity, * was in mood for that. So...any other s...
5572   ham  The guy did some bitching but I acted like i'd...
5573   ham                         Rofl. Its true to its name

[5574 rows x 2 columns]
```

2. EXPLORATORY DATA ANALYSIS

```
# for information of columns names dtype and for counts of null
objects
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5574 entries, 0 to 5573
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   type    5574 non-null   object
 1   text    5574 non-null   object
dtypes: object(2)
memory usage: 87.2+ KB
```

```
# for above 5 rows
df.head()
```

```
   type                                                text
0   ham  Go until jurong point, crazy.. Available only ...
1   ham                      Ok lar... Joking wif u oni...
2  spam  Free entry in 2 a wkly comp to win FA Cup fina...
3   ham  U dun say so early hor... U c already then say...
4   ham  Nah I don't think he goes to usf, he lives aro...
```

```
# fr belows 5 rows
df.tail()
```

```
      type                                                text
5569  spam  This is the 2nd time we have tried 2 contact u...
5570   ham                Will ü b going to esplanade fr home?
5571   ham  Pity, * was in mood for that. So...any other s...
5572   ham  The guy did some bitching but I acted like i'd...
5573   ham                         Rofl. Its true to its name
```

```
#for stastical values
df.describe()
```

```
        type                    text
count   5574                    5574
unique     2                    5160
top      ham  Sorry, I'll call later
freq    4827                      30
```

```
#checking the null values presented in our dataset
df.isnull().sum()
```

```
type    0
text    0
dtype: int64
```

2.1 VISUALIZE DATASET

```
# Let's see which message is the most popular ham/spam message
df.groupby('type').describe()
```

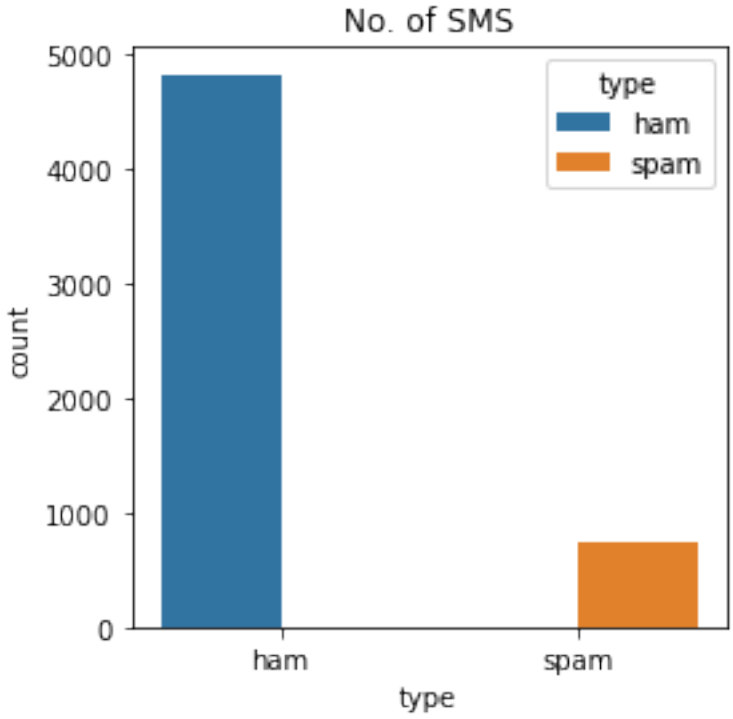
```
      text
```

```
     count unique                                                top
freq
type

ham   4827   4518                                Sorry, I'll call later
30
spam   747    642  Please call our customer service representativ...
4
```

DATA IS CLEARED NO WE ABLE TO DO FURTHER PROCESS

2.2 DATA VISUALIZATION

```
plt.figure(figsize = (4,4))
sns.countplot(x ="type", data = df, hue ="type")
plt.title("No. of SMS")
plt.show()
```

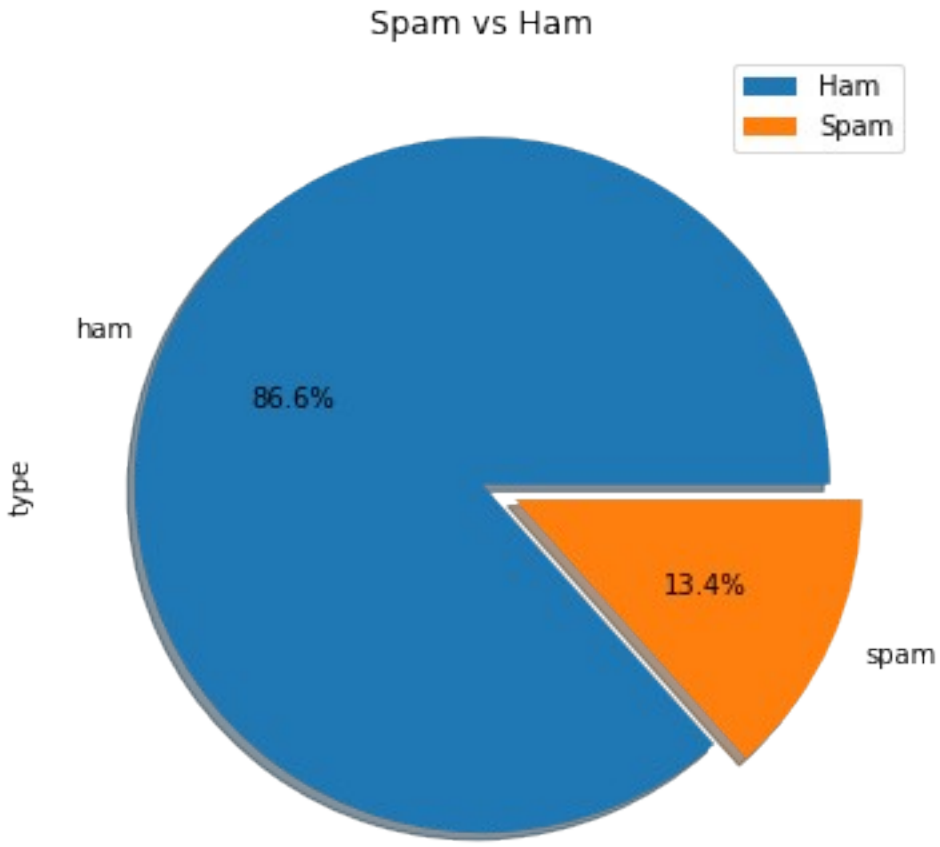



```
df["text"].value_counts()
```

```
Sorry, I'll call later
30
I cant pick the phone right now. Pls send a message
12
Ok...
10
Ok
4
Ok.
4


..
I gotta collect da car at 6 lei.
1
No. On the way home. So if not for the long dry spell the season would
have been over
```

```
1
Urgent! Please call 09061743811 from landline. Your ABTA complimentary
4* Tenerife Holiday or £5000 cash await collection SAE T&Cs Box 326
CW25WX 150ppm     1
I think asking for a gym is the excuse for lazy people. I jog.
1
Rofl. Its true to its name
1
Name: text, Length: 5160, dtype: int64
```

```
df["type"].value_counts().plot(kind = 'pie',explode=[0,
0.1],figsize=(6, 6),autopct='%1.1f%%',shadow=True)
plt.title("Spam vs Ham")
plt.legend(["Ham", "Spam"])
plt.show()
```



A lot of messages are actually not spam. About 86% of our dataset consists of normal messages

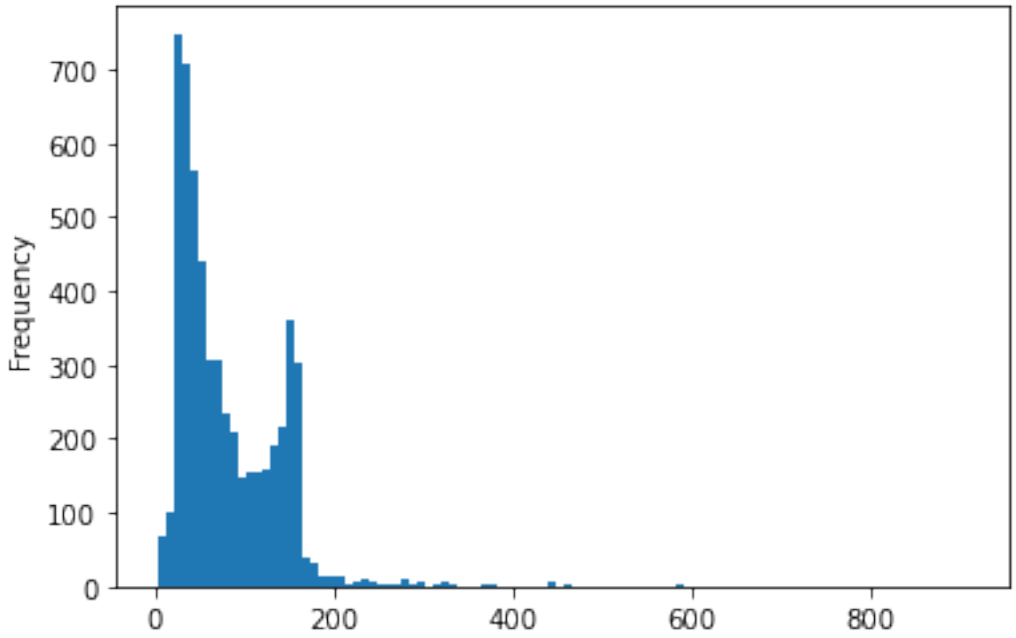
2.3 ADDING A NEW COLUMN LENGTH IN DATASET

```
# Let's get the length of the messages
df['length'] = df['text'].apply(len)
df.head()
```

	type	text	length
0	ham	Go until jurong point, crazy.. Available only ...	111
1	ham	Ok lar... Joking wif u oni...	29
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	155
3	ham	U dun say so early hor... U c already then say...	49
4	ham	Nah I don't think he goes to usf, he lives aro...	61

```
df['length'].plot(bins=100, kind='hist')
```

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




```
df.length.describe()
```

```
count    5574.000000
mean       80.444923
std        59.841828
min         2.000000
25%        36.000000
50%        61.000000
75%       122.000000
max       910.000000
Name: length, dtype: float64
```

```
# Let's see the longest message 43952
df[df['length'] == 910]['text'].iloc[0]
```

```
"For me the love should start with attraction.i should feel that I
need her every time around me.she should be the first thing which
comes in my thoughts.I would start the day and end it with her.she
should be there every time I dream.love will be then when my every
breath has her name.my life should happen around her.my life will be
named to her.I would cry for her.will give all my happiness and take
all her sorrows.I will be ready to fight with anyone for her.I will be
in love when I will be doing the craziest things for her.love will be
when I don't have to proove anyone that my girl is the most beautiful
lady on the whole planet.I will always be singing praises for her.love
will be when I start up making chicken curry and end up makiing
sambar.life will be the most beautiful then.will get every morning and
thank god for the day because she is with me.I would like to say a
lot..will tell later.."
```

the above message was the longest message in our dataset

```
# Let seperate the data as ham and spam
ham = df[df['type']=='ham']
spam = df[df['type']=='spam']

ham.head()
```

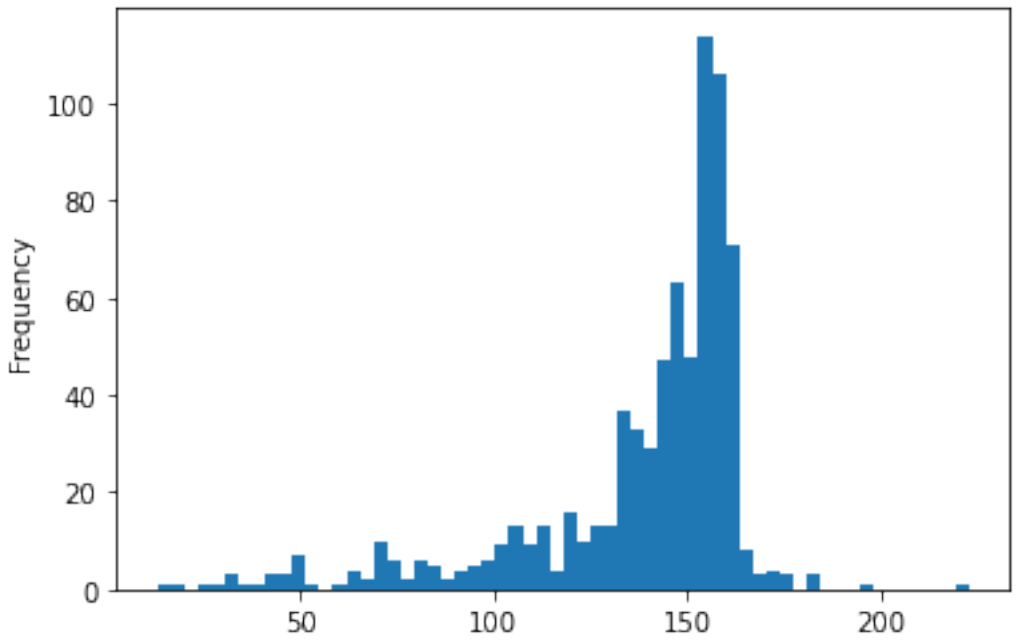
	type	text	length
0	ham	Go until jurong point, crazy.. Available only ...	111
1	ham	Ok lar... Joking wif u oni...	29
3	ham	U dun say so early hor... U c already then say...	49
4	ham	Nah I don't think he goes to usf, he lives aro...	61
6	ham	Even my brother is not like to speak with me. ...	77

```
spam.head()
```

	type	text	length
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	155
5	spam	FreeMsg Hey there darling it's been 3 week's n...	147
8	spam	WINNER!! As a valued network customer you have...	157
9	spam	Had your mobile 11 months or more? U R entitle...	154
11	spam	SIX chances to win CASH! From 100 to 20,000 po...	136

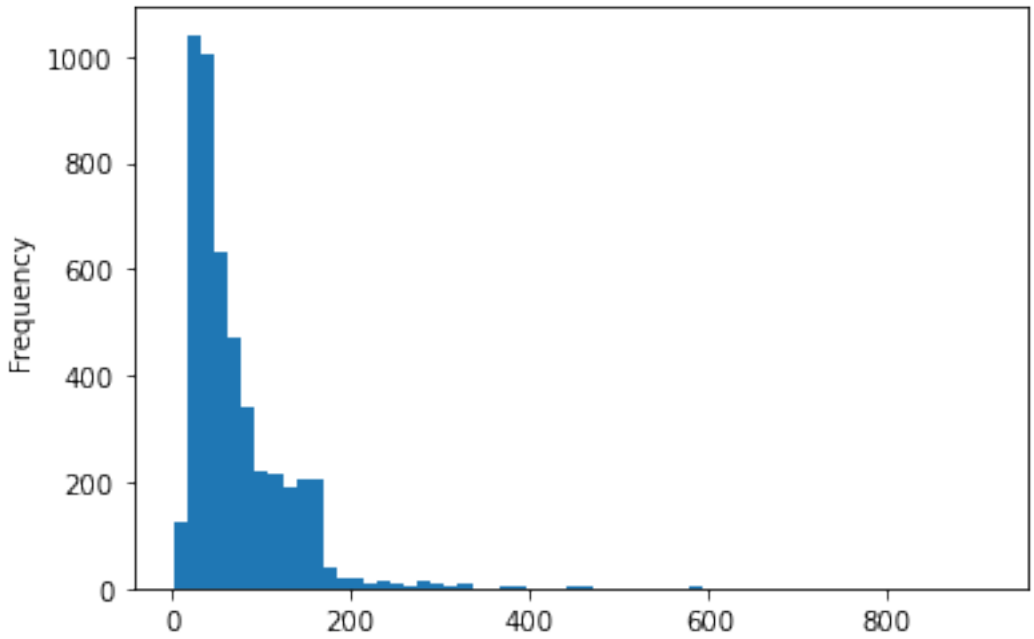
```
# Let visualize it by hist plot
spam['length'].plot(bins=60, kind='hist')
```

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




```
ham['length'].plot(bins=60, kind='hist')
```

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




```
# let see the percentage wise distribution of ham and spam in
dataframe
print( 'Spam percentage =', (len(spam) / len(df) )*100,"%")
print( 'Ham percentage =', (len(ham) / len(df) )*100,"%")
```

```
Spam percentage = 13.40150699677072 %
Ham percentage = 86.59849300322928 %
```

IN OUR DATASET Ham MESSAGES IS 86.5% WHICH IS VERY LARGE AMOUNT

3. CREATE TESTING AND TRAINING DATASET / DATA CLEANING

3.1 REMOVE PUNCTUATION

```
# importing string punctuation
import string
string.punctuation
```

```
'!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'
```

```
# Lets test the data by some value before using it
text='Hello Mr. Future, I am a beginner learner in a field of Machine
Learning now!'

# let remove the punctuation from the text
text_punc_removed=[char for char in text if char not in
string.punctuation]
print(text_punc_removed)
```

```
['H', 'e', 'l', 'l', 'o', ' ', 'M', 'r', ' ', 'F', 'u', 't', 'u', 'r',
'e', ' ', 'I', ' ', 'a', 'm', ' ', 'a', ' ', 'b', 'e', 'g', 'i', 'n',
'n', 'e', 'r', ' ', 'l', 'e', 'a', 'r', 'n', 'e', 'r', ' ', 'i', 'n',
' ', 'a', ' ', 'f', 'i', 'e', 'l', 'd', ' ', 'o', 'f', ' ', 'M', 'a',
'c', 'h', 'i', 'n', 'e', ' ', 'L', 'e', 'a', 'r', 'n', 'i', 'n', 'g',
' ', 'n', 'o', 'w']
```

```
# joining the character to make a sentence
test_joined = ''.join(text_punc_removed)
test_joined
```

```
'Hello Mr Future I am a beginner learner in a field of Machine
Learning now'
```

AS WE SEE NOW ALL PUNCTUATION GET REMOVED SO WE USE IT NOW

3.2 REMOVE STOPWORDS

```
# Download stopwords Package to execute this command
import nltk
nltk.download('stopwords')
```

```
from nltk.corpus import stopwords
stopwords.words('english')
print()
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\admin\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
# let conver all to lower case
Test_punc_removed_join_clean = [word for word in test_joined.split()
if word.lower() not in stopwords.words('english')]

Test_punc_removed_join_clean # Only important (no so common) words are
left
```

```
['Hello',
 'Mr',
 'Future',
 'beginner',
 'learner',
 'field',
 'Machine',
 'Learning']
```

3.3 COUNT VECTORIZER EXAMPLE

```
# IMPORT THE COUNT VECTORIZER LIBRARY
from sklearn.feature_extraction.text import CountVectorizer
sample_data = [' This is the first document.','This document is the
second document.','And this is the third one.','Is this the first
document?']

vectorizer = CountVectorizer()
X = vectorizer.fit_transform(sample_data)

print(vectorizer.get_feature_names())
```

```
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third',
'this']
```

```
print(X.toarray())
```

```
[[0 1 1 1 0 0 1 0 1]
 [0 2 0 1 0 1 1 0 1]
 [1 0 0 1 1 0 1 1 1]
 [0 1 1 1 0 0 1 0 1]]
```

4. USING PIPELINE FOR APPLICATION

4.1 APPLYING THE PREVIOUSLY THREE PROCESS TO OUR SPAM OR HAM EXAMPLES

```
# Define a pipeline to clean up all the messages
# The pipeline performs the following: (1) remove punctuation, (2)
remove stopwords

def message_cleaning(message):
    Test_punc_removed = [char for char in message if char not in
string.punctuation]
    Test_punc_removed_join = ''.join(Test_punc_removed)
    Test_punc_removed_join_clean = [word for word in
Test_punc_removed_join.split() if word.lower() not in
stopwords.words('english')]
    return Test_punc_removed_join_clean

# Test the newly added function
spam_df_clean = df['text'].apply(message_cleaning)

# Let print a message by cleaning
print(spam_df_clean[0])
```

```
['Go', 'jurong', 'point', 'crazy', 'Available', 'bugis', 'n', 'great',
'world', 'la', 'e', 'buffet', 'Cine', 'got', 'amore', 'wat']
```

```
# Original message without any filter
print(df['text'][0])
```

```
Go until jurong point, crazy.. Available only in bugis n great world
la e buffet... Cine there got amore wat...
```

5. APPLYING COUNT VECTORIZER TO OUR MESSAGE LIST

```
# IMPORT LIBRARY
from sklearn.feature_extraction.text import CountVectorizer

# Define the cleaning pipeline we defined earlier
vectorizer = CountVectorizer(analyzer = message_cleaning)

# PASSING OUR Texts
spamham_countvectorizer = vectorizer.fit_transform(df['text'])

#print(vectorizer.get_feature_names())

print(spamham_countvectorizer.toarray())
```

```
[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

```
spamham_countvectorizer.shape
```

```
(5574, 11401)
```

6. TRAINING THE MODEL WITH ALL DATASET

6.1 USING NAIVE BAYES MULTINOMIALNB METHOD

```
# Importing library multinomialDB from naive bayes
from sklearn.naive_bayes import MultinomialNB

NB_classifier = MultinomialNB()
label = df['type'].values
NB_classifier.fit(spamham_countvectorizer, label)
```

```
MultinomialNB()
```

```
# testing_sample = ['Free money!!!', "Hi Kim, Please let me know if
you need any further information. Thanks"]
testing_sample = ["""'Free money!!!', "Hi Kim, Please let me know if
you need any further information. Thanks""","""Free entry in 2 a wkly
comp to win FA Cup final tkts 21st May 2005. Text FA to 87121 to
receive entry question(std txt rate)T&C's apply
08452810075over18's"""]

testing_sample_countvectorizer = vectorizer.transform(testing_sample)

# PREDECTING ABOVE TEXT WAS HAM/SPAM
test_predict = NB_classifier.predict(testing_sample_countvectorizer)
test_predict
```

```
array(['ham', 'spam'], dtype='<U4')
```

```
# Mini Challenge!
testing_sample = ['Hello, I am Ryan, I would like to book a hotel in
Bali by January 24th', 'money viagara!!!!!']

testing_sample = ['money viagara!!!!!', "Hello, I am Ryan, I would
like to book a hotel in SF by January 24th"]
testing_sample_countvectorizer = vectorizer.transform(testing_sample)
```

```
test_predict = NB_classifier.predict(testing_sample_countvectorizer)
test_predict
```

```
array(['ham', 'ham'], dtype='<U4')
```

7. DIVIDEING THE DATA INTO TRAINING AND TESTING PRIOR TO TRAINING

```
x = spamham_countvectorizer
y = label

# x will always required 2d
x.shape
```

```
(5574, 11401)
```

```
# y is our target colum in 1d
y.shape
```

```
(5574,)
```

```
# splitinhg the data as test and train data
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2)

from sklearn.naive_bayes import MultinomialNB

NB_classifier = MultinomialNB()
NB_classifier.fit(xtrain, ytrain)
```

```
MultinomialNB()
```

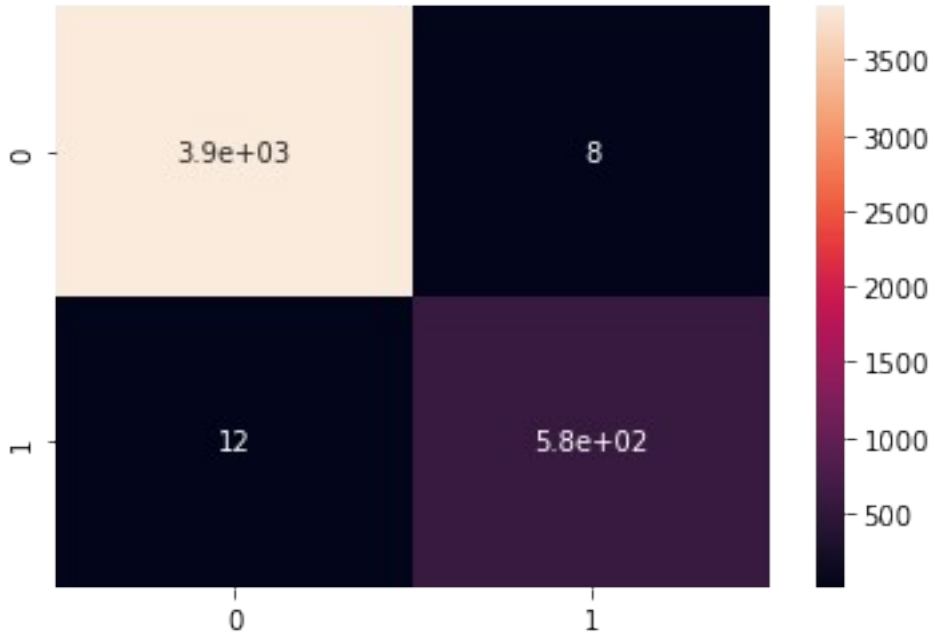
8. EVALUATING THE MODEL

```
# this library help to make a classificaion reports
from sklearn.metrics import classification_report, confusion_matrix
```

8.1 PREDECTING DATA ON TRAIN DATA BY USING CONFUSION MATRIX

```
y_predict_train = NB_classifier.predict(xtrain)
y_predict_train
cm = confusion_matrix(ytrain, y_predict_train)
sns.heatmap(cm, annot=True)
```

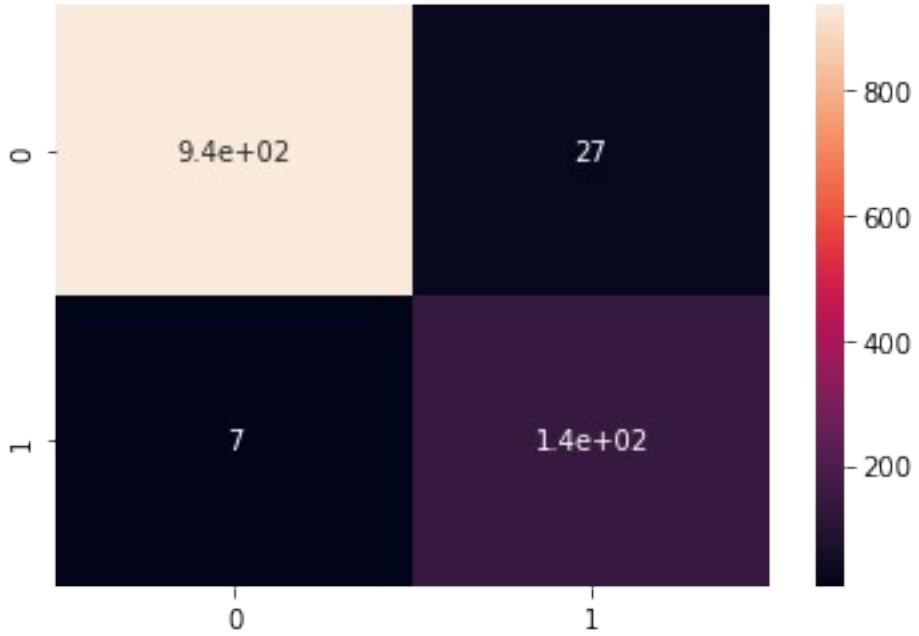
```
<AxesSubplot:>
```



8.2 PREDECTING DATA ON TEST DATA BY USING CONFUSION MATRIX

```
# Predicting the Test set results
y_predict_test = NB_classifier.predict(xtest)
cm = confusion_matrix(ytest, y_predict_test)
sns.heatmap(cm, annot=True)
```

```
<AxesSubplot:>
```



```
cm
```

```
array([[936,  27],
       [  7, 145]], dtype=int64)
```

```
# Printing a classification report

nbaccuracy = round(accuracy_score(ytest, y_predict_test) * 100, 2)
print(f'NB Classifier Accuracy on test data {nbaccuracy}')
print(classification_report(ytest, y_predict_test))
print(f'The accuracy achieved from NB Classifier on test data is :
{nbaccuracy}\n\n')
```

```
NB Classifier Accuracy on test data 96.95
              precision    recall  f1-score   support

         ham       0.99      0.97      0.98       963
        spam       0.84      0.95      0.90       152

    accuracy                           0.97      1115
   macro avg       0.92      0.96      0.94      1115
weighted avg       0.97      0.97      0.97      1115

The accuracy achieved from NB Classifier on test data is : 96.95
```

9. LET'S ADD ADDITIONAL FEATURE TF-IDF

```
spamham_countvectorizer
```

```
<5574x11401 sparse matrix of type '<class 'numpy.int64'>'
     with 50544 stored elements in Compressed Sparse Row format>
```

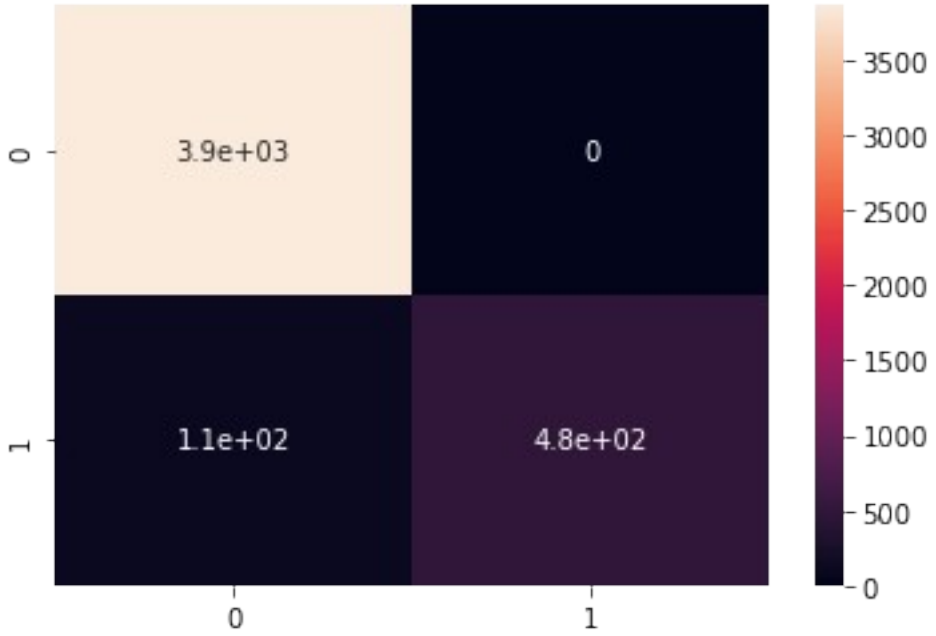
```
from sklearn.feature_extraction.text import TfidfTransformer

emails_tfidf =
TfidfTransformer().fit_transform(spamham_countvectorizer)
print(emails_tfidf.shape)
```

```
(5574, 11401)
```

```
#print(emails_tfidf[:,:])
# Sparse matrix with all the values of IF-IDF

X = emails_tfidf
y = label

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)

from sklearn.naive_bayes import MultinomialNB
NB_classifier = MultinomialNB()
NB_classifier.fit(X_train, y_train)

from sklearn.metrics import classification_report, confusion_matrix
y_predict_train = NB_classifier.predict(X_train)
y_predict_train
cm = confusion_matrix(y_train, y_predict_train)
sns.heatmap(cm, annot=True)
```

```
<AxesSubplot:>
```




```
NB_classifier_accuracy = round(accuracy_score(y_test, y_predict_test)
* 100, 2)
print(f'NB Classifier Accuracy {NB_classifier_accuracy}')
print(classification_report(y_test, y_predict_test))
print(f'The accuracy achieved from NB Classifier on test data is :
{NB_classifier_accuracy}\n\n')
```

```
NB Classifier Accuracy 74.62
              precision    recall  f1-score   support

         ham       0.86      0.84      0.85       962
        spam       0.12      0.14      0.13       153

    accuracy                           0.75      1115
   macro avg       0.49      0.49      0.49      1115
```

```
weighted avg       0.76      0.75      0.75      1115

The accuracy achieved from NB Classifier on test data is : 74.62
```

10. MODEL TRAINING BY USING MACHINE LEARNING ALGORITHM

10.1 - Finding the Accuracy of data by using Logistic Regression

```
# Logistic Regression
from sklearn.linear_model import LogisticRegression

logistic_regression_model = LogisticRegression(random_state=42)
logistic_regression_model.fit(xtrain, ytrain)

LogisticRegression(random_state=42)

y_pred = logistic_regression_model.predict(xtest)
acc_logreg = round(accuracy_score(y_pred, ytest) * 100, 2)
print(f'Logistic Regression accuracy {acc_logreg}')
print(classification_report(ytest,y_pred))                  #printing
the report of classification
print(f'The accuracy achieved from Logistic Regression is :
{acc_logreg}\n\n')

Logistic Regression accuracy 97.49
              precision    recall  f1-score   support

         ham       0.97      1.00      0.99       963
        spam       1.00      0.82      0.90       152

    accuracy                           0.97      1115
   macro avg       0.99      0.91      0.94      1115
weighted avg       0.98      0.97      0.97      1115

The accuracy achieved from Logistic Regression is : 97.49
```

10.2 - Finding the Accuracy of data by using Decission Tree Classifier

```
#Decision Tree
from sklearn.tree import DecisionTreeClassifier

decisiontree_model = DecisionTreeClassifier(random_state=42)
decisiontree_model.fit(xtrain, ytrain)
```

```
DecisionTreeClassifier(random_state=42)

y_pred = decisiontree_model.predict(xtest)
acc_decisiontree = round(accuracy_score(ytest,y_pred) * 100, 2)
print(f'Decision Tree Classifier accuracy {acc_decisiontree: .2f}')
print(classification_report(ytest, y_pred))
print(f'The accuracy achieved from Decision Tree Classifier is :
{acc_decisiontree}\n\n')
```

```
Decision Tree Classifier accuracy  96.95
              precision    recall  f1-score   support

         ham       0.98      0.99      0.98       963
        spam       0.92      0.85      0.88       152

    accuracy                           0.97      1115
   macro avg       0.95      0.92      0.93      1115
weighted avg       0.97      0.97      0.97      1115

The accuracy achieved from Decision Tree Classifier is : 96.95
```

10.3 - Finding the Accuracy of data by using Random Forest Classifier

```
# Random Forest
from sklearn.ensemble import RandomForestClassifier

random_forest_model = RandomForestClassifier(random_state=42)
random_forest_model.fit(xtrain, ytrain)

RandomForestClassifier(random_state=42)

predictions = random_forest_model.predict(xtest)
ranfor_accuracy = accuracy_score(ytest, predictions)
print(f"Random Forest Classifier Accuracy: {ranfor_accuracy:.2f}")
print(classification_report(ytest, predictions))
print(f'The accuracy achieved from Random Forest Classifier is :
{ranfor_accuracy*100}\n\n')
```

```
Random Forest Classifier Accuracy: 0.97
              precision    recall  f1-score   support

         ham       0.96      1.00      0.98       963
        spam       1.00      0.75      0.86       152

    accuracy                           0.97      1115
   macro avg       0.98      0.88      0.92      1115
weighted avg       0.97      0.97      0.96      1115

The accuracy achieved from Random Forest Classifier is :
```

```
96.59192825112108
```

10.4 - Finding the Accuracy of data by using Encemble Learning - Ada Boost Classifier

```
from sklearn.ensemble import AdaBoostClassifier
ada = AdaBoostClassifier()
ada.fit(xtrain,ytrain)
ypred = ada.predict(xtest)
ada_boost_accuracy = accuracy_score(ytest, ypred)
print(f'Ada Boost Accuracy: {ada_boost_accuracy*100:.2f}')
print(classification_report(ytest,ypred))
print(f'The accuracy achieved from Ada Boost Classifier is :
{ada_boost_accuracy*100}\n\n')
```

```
Ada Boost Accuracy: 96.59
              precision    recall  f1-score   support

         ham       0.96      1.00      0.98       963
        spam       0.97      0.77      0.86       152

    accuracy                           0.97      1115
   macro avg       0.97      0.88      0.92      1115
weighted avg       0.97      0.97      0.96      1115

The accuracy achieved from Ada Boost Classifier is : 96.59192825112108
```

10.5 - Predicting by using Naive Bayes classifier

```
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix

accuracy = accuracy_score(ytest, ypred)
conf_matrix = confusion_matrix(ytest, ypred)
classification_rep = classification_report(ytest, ypred)
print(f'The accuracy achieved from Ada Boost Classifier is :
{accuracy*100}\n\n')
print("\nConfusion Matrix:\n", conf_matrix)
print("\nClassification Report:\n", classification_rep)
print(f'The accuracy achieved from Naive Bayes Classifier is :
{accuracy*100}\n\n')
```

```
The accuracy achieved from Ada Boost Classifier is : 96.59192825112108
```

```
Confusion Matrix:
 [[960   3]
 [ 35 117]]

Classification Report:
              precision    recall  f1-score   support

         ham       0.96      1.00      0.98       963
        spam       0.97      0.77      0.86       152

    accuracy                           0.97      1115
   macro avg       0.97      0.88      0.92      1115
weighted avg       0.97      0.97      0.96      1115

The accuracy achieved from Naive Bayes Classifier is :
96.59192825112108
```

we got the accuracy of different modules of classifier

```
print(f'The accuracy achieved from NB Classifier on test data is :
{NB_classifier_accuracy}\n')
print(f'The accuracy achieved from NB Classifier on train data is :
{nbaccuracy}\n')
print(f'The accuracy achieved from Logistic Regression is :
{acc_logreg}\n')
print(f'The accuracy achieved from Decision Tree Classifier is :
{acc_decisiontree}\n')
print(f'The accuracy achieved from Random Forest Classifier is :
{ranfor_accuracy*100}\n')
print(f'The accuracy achieved from Ada Boost Classifier is :
{ada_boost_accuracy*100}\n')
print(f'The accuracy achieved from Naive Bayes Classifier is :
{accuracy*100}\n')
```

```
The accuracy achieved from NB Classifier on test data is : 74.62

The accuracy achieved from NB Classifier on train data is : 96.95

The accuracy achieved from Logistic Regression is : 97.49

The accuracy achieved from Decision Tree Classifier is : 96.95

The accuracy achieved from Random Forest Classifier is :
96.59192825112108

The accuracy achieved from Ada Boost Classifier is : 96.59192825112108

The accuracy achieved from Naive Bayes Classifier is :
```

```
96.59192825112108
```

CONCLUSION

```
print(("*")*125)
print(f' As we see during the prediction the accuracy achieved from
Logistic Regression classifiern is {acc_logreg} Which was much good as
compare to another, So we can go throung Logistic Regression modules
for prediction')
print(("*")*125)
print(f"\tBased on the above accuracy scores, we should go ahead with
\n\nNB Classifier on test data is : {NB_classifier_accuracy},\n\nNB
Classifier on train data is : {nbaccuracy},\n\nLogistic Regression :
{acc_logreg},\n\nDecision Tree Classifier : {acc_decisiontree},\n\
nRandom Forest Classifier : {ranfor_accuracy*100},\n\nAccuracy with
Ada Boost Classifier : {ada_boost_accuracy*100}\n\nAccuracy with Naive
Bayes Classifier : {accuracy*100}\n\n The best predictive model for
the above dataset is Logistic Regression Classifier and its Accuracy
is {acc_logreg}. So Logistic Regression Classifier is best for Spam
and Ham message classification ")
print(("*")*125)

print(("*")*125)
```

```
**************************************************************************
**********************************************************
 As we see during the prediction the accuracy achieved from Logistic
Regression classifiern is 97.49 Which was much good as compare to
another, So we can go throung Logistic Regression modules for
prediction
**************************************************************************
**********************************************************
     Based on the above accuracy scores, we should go ahead with

NB Classifier on test data is : 74.62,

NB Classifier on train data is : 96.95,

Logistic Regression :97.49,

Decision Tree Classifier : 96.95,

Random Forest Classifier : 96.59192825112108,

Accuracy with Ada Boost Classifier : 96.59192825112108

Accuracy with Naive Bayes Classifier : 96.59192825112108
```

```
 The best predictive model for the above dataset is Logistic
Regression Classifier and its Accuracy is 97.49. So Logistic
Regression Classifier is best for Spam and Ham message classification
**********************************************************************
**************************************************
**********************************************************************
**************************************************
```