Report

TOPIC: FAKE NEWS DETECTION USING MACHINE LEARNING

Introduction

Data has been increasing at an unprecedented range in an exponential manner and is producing 2.7 quintillion bytes of data everyday.

The definition of fake news is information that pushes people down the wrong road. Fake news is spreading like wildfire these days, and people are sharing it without confirming it. This is frequently done to promote or impose specific views, and it is frequently accomplished through political agendas.

As a result, it is vital to recognise fake news.

Problem Definition:

Fake News have become more prevalent in recent years and with great amount of dynamism in internet and social media, differentiating between facts and opinions, relating to commercial or political upheavals has become more difficult than ever.

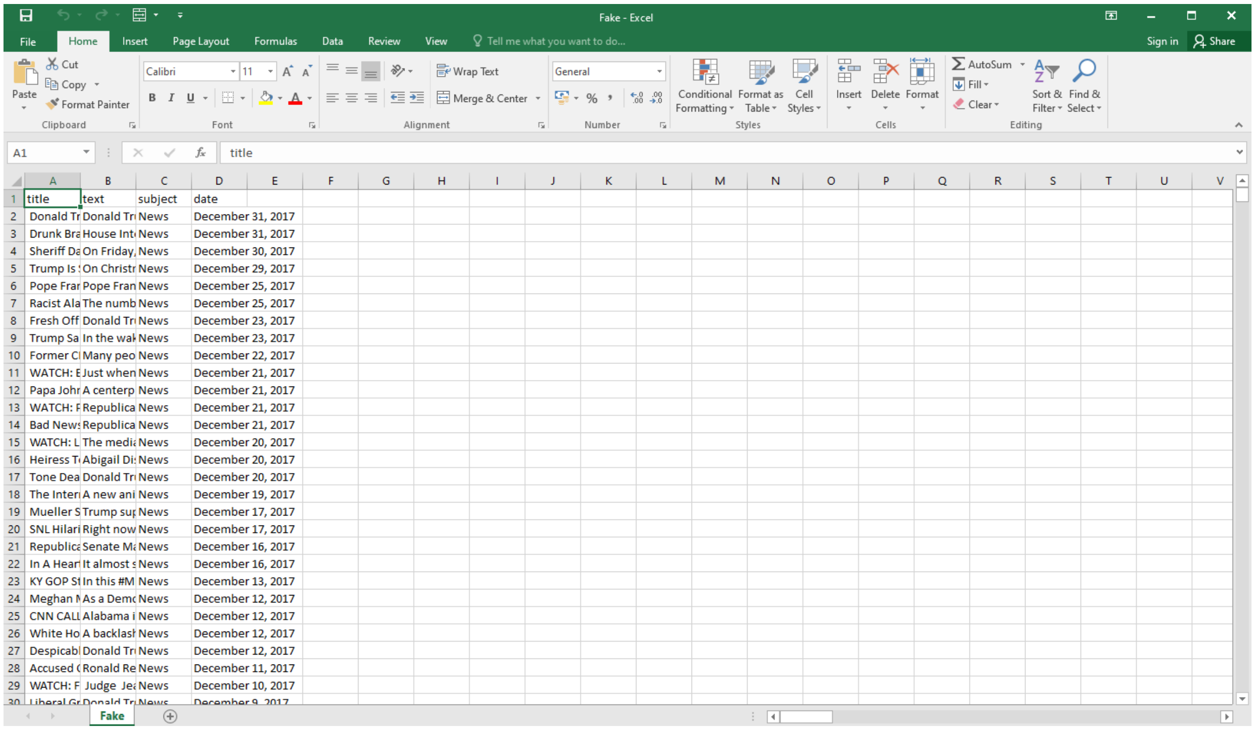
Fake information is purposely or unintentionally spread throughout the internet. The massive dissemination of fake news has left an indelible mark on people and culture.

We use various NLP and preprocessing methodologies like tokenization, stop words removal, lemmatization, stemming and machine learning classification algorithms - logistic regression, pac, ada, naive bayes, svm, random forest, xgboost, decision trees and rnn, to build a model that differentiates between fake news and real news and also analyze the performance of these various classification methodologies to choose the best classifier on out dataset.

Dataset:

We have used the ISOT dataset which can be downloaded from - https://www.uvic.ca/ecs/ece/isot/datasets/index.php

1. Fake news DataSet



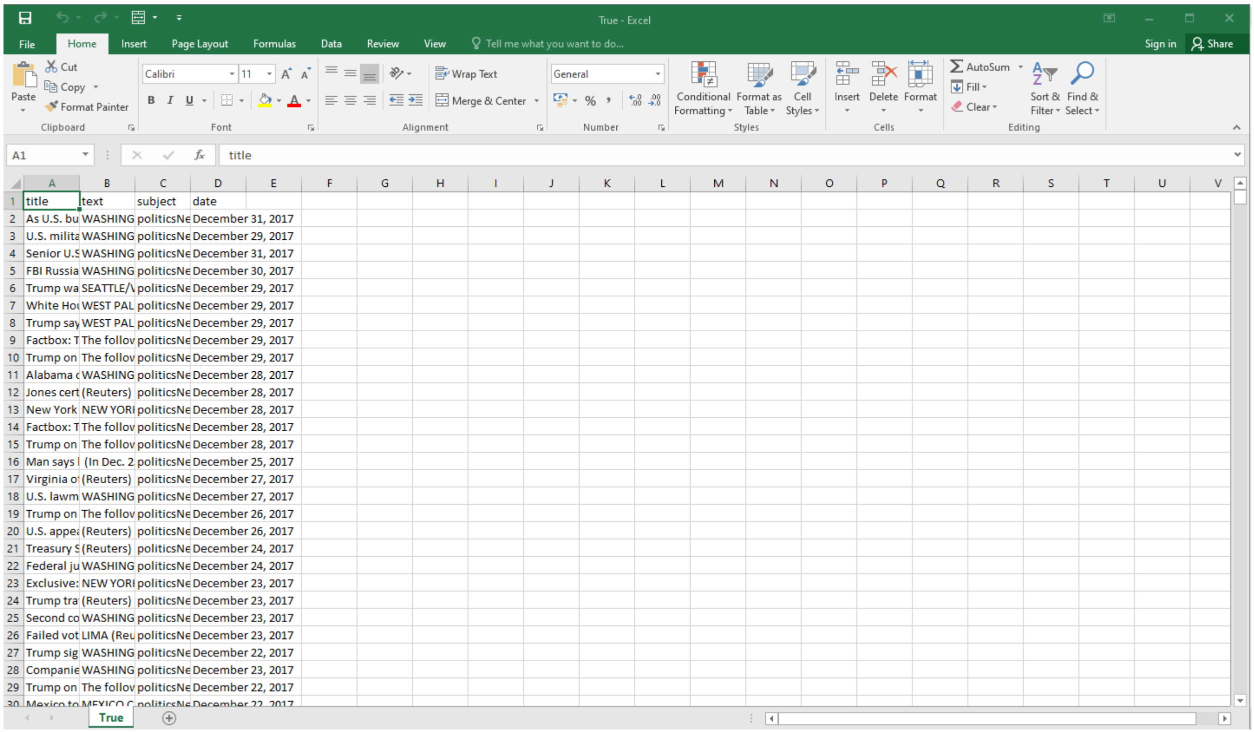
title	text	subject	date
Donald Tr	Donald Tr	News	December 31, 2017
Drunk Bra	House Inte	News	December 31, 2017
Sheriff Da	On Friday,	News	December 30, 2017
Trump Is	On Christr	News	December 29, 2017
Pope Frar	Pope Fran	News	December 25, 2017
Racist Ala	The numb	News	December 25, 2017
Fresh Off	Donald Tr	News	December 23, 2017
Trump Sa	In the wak	News	December 23, 2017
Former C	Many peo	News	December 22, 2017
WATCH: E	Just when	News	December 21, 2017
Papa Johr	A centerp	News	December 21, 2017
WATCH: F	Republica	News	December 21, 2017
Bad News	Republica	News	December 21, 2017
WATCH: L	The media	News	December 20, 2017
Heiress T	Abigail Di	News	December 20, 2017
Tone Dea	Donald Tr	News	December 20, 2017
The Interi	A new ani	News	December 19, 2017
Mueller S	Trump sup	News	December 17, 2017
SNL Hilari	Right now	News	December 17, 2017
Republica	Senate Ma	News	December 16, 2017
In A Hear	It almost s	News	December 16, 2017
KY GOP St	In this #M	News	December 13, 2017
Meghan M	As a Demo	News	December 12, 2017
CNN CALL	Alabama i	News	December 12, 2017
White Ho	A backlash	News	December 12, 2017
Despicabl	Donald Tr	News	December 12, 2017
Accused (	Ronald Re	News	December 11, 2017
WATCH: F	Judge Jea	News	December 10, 2017
Liberal Gr	Donald Tr	News	December 9, 2017

Rows: 23481

Columns: 4

Column Description: The four columns include the title of the news, the text in the news, the subject of the news and the date of the news.

2. True news DataSet



	A	B	C	D
1	title	text	subject	date
2	As U.S. bu	WASHING	politicsNe	December 31, 2017
3	U.S. milita	WASHING	politicsNe	December 29, 2017
4	Senior U.S	WASHING	politicsNe	December 31, 2017
5	FBI Russia	WASHING	politicsNe	December 30, 2017
6	Trump wa	SEATTLE/\	politicsNe	December 29, 2017
7	White Hou	WEST PAL	politicsNe	December 29, 2017
8	Trump say	WEST PAL	politicsNe	December 29, 2017
9	Factbox: T	The follov	politicsNe	December 29, 2017
10	Trump on	The follov	politicsNe	December 29, 2017
11	Alabama c	WASHING	politicsNe	December 28, 2017
12	Jones cert	(Reuters)	politicsNe	December 28, 2017
13	New York	NEW YORI	politicsNe	December 28, 2017
14	Factbox: T	The follov	politicsNe	December 28, 2017
15	Trump on	The follov	politicsNe	December 28, 2017
16	Man says l	(In Dec. 2	politicsNe	December 25, 2017
17	Virginia of	(Reuters)	politicsNe	December 27, 2017
18	U.S. lawm	WASHING	politicsNe	December 27, 2017
19	Trump on	The follov	politicsNe	December 26, 2017
20	U.S. appea	(Reuters)	politicsNe	December 26, 2017
21	Treasury S	(Reuters)	politicsNe	December 24, 2017
22	Federal ju	WASHING	politicsNe	December 24, 2017
23	Exclusive:	NEW YORI	politicsNe	December 23, 2017
24	Trump tra	(Reuters)	politicsNe	December 23, 2017
25	Second co	WASHING	politicsNe	December 23, 2017
26	Failed vot	LIMA (Reu	politicsNe	December 23, 2017
27	Trump sig	WASHING	politicsNe	December 22, 2017
28	Companie	WASHING	politicsNe	December 23, 2017
29	Trump on	The follov	politicsNe	December 22, 2017
30	Mexico to	MEXICO C	politicsNe	December 22, 2017

Rows: 21417

Columns: 4

Column Description: The four columns include the title of the news, the text in the news, the subject of the news and the date of the news

Implementation:

1. Importing relevant libraries

▾ Importing the required libraries

```
#dataset handling and operations
from google.colab import drive
import re,string,unicodedata
import numpy as np
import pandas as pd

#visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('bmh')
from wordcloud import WordCloud, STOPWORDS

#nlp pre-processing
from sklearn.utils import shuffle
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from nltk.stem.porter import PorterStemmer
from nltk.corpus import wordnet

#vectorizers and splitting
```

```
[ ]
#vectorizers and splitting
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelBinarizer

#models
from sklearn.linear_model import LogisticRegression
from xgboost import XGBClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import svm,naive_bayes
from sklearn.linear_model import PassiveAggressiveClassifier
from sklearn.ensemble import AdaBoostClassifier

#metrics
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
from sklearn.metrics import plot_confusion_matrix,precision_score,f1_score,recall_score,plot_roc_curve

#for rnn-lstm
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
```

```
[ ] nltk.download('stopwords')
    nltk.download('punkt')
    nltk.download('wordnet')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
True
```

2. Our dataset is uploaded on Google Drive. To read the dataset, we mount our drive by authorizing the google account and then moving to the folder where our dataset is present using '%cd'. We check for the folder content using '!ls'

Loading the datasets from Google Drive

```
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
[ ] %cd /content/drive/My Drive/fakenews/
```

```
/content/drive/My Drive/fakenews
```

```
[ ] !ls
```

```
Fake.csv   True.csv
```

3. Now that our drive has been mounted, we read the dataset. We have two different datasets for Fake and True news. The fake news database consists of 23481 items and the true news dataset contains 21417 items. We display a few records using the sample() function.

Reading the input CSV files

```
[ ] fake_df = pd.read_csv('Fake.csv')
    true_df = pd.read_csv('True.csv')
```

```
[ ] fake_df.shape
```

```
(23481, 4)
```

```
[ ] true_df.shape
```

```
(21417, 4)
```

```
[ ] fake_df.sample(5)
```

```
[ ] fake_df.sample(5)
```

	title	text	subject	date
9458	TRUMP REPORTEDLY Thinking About Replacing Jeff...	Hillary Clinton, Barack Obama, Eric Holder and...	politics	Nov 11, 2017
8866	Cruz Dedicates Empty Seat At State Of The Uni...	Yesterday, President Barack Obama made a touch...	News	January 9, 2016
10390	FLASHBACK: ARMY OF WOMEN Join Social Media Cra...	President Trump and his daughter Ivanka are ge...	politics	Jul 16, 2017
15809	MUST WATCH VIDEO: LISTEN TO OBAMA AND HIS COMM...	OBAMA SPEAKS ABOUT FRANK AND HIS MENTOR WHO SC...	politics	Apr 19, 2015
9041	Tired Of Things Going Well, Marco Rubio Makes...	Listening to several of the Republican candida...	News	January 1, 2016

```
[ ] true_df.sample(5)
```

	title	text	subject	date
8687	China upset by U.S. Republican platform on Sou...	BEIJING (Reuters) - China's Foreign Ministry o...	politicsNews	July 21, 2016
7371	U.S. voters say yes to big bond issues, mixed ...	(Reuters) - U.S. voters on Tuesday favored a s...	politicsNews	November 9, 2016
14355	Gerry Adams to step down in end of an era for ...	DUBLIN (Reuters) - Sinn Fein s Gerry Adams, a ...	worldnews	November 18, 2017
1462	Rich would benefit most from Trump tax cut pla...	WASHINGTON (Reuters) - The wealthiest American...	politicsNews	September 29, 2017
18967	U.S. welcomes royal order to allow Saudi women...	WASHINGTON (Reuters) - The United States on Tu...	worldnews	September 26, 2017

4. We check for null values in both datasets.

Checking for null values

```
fake_df.isna().sum()
```

```
title      0
text       0
subject    0
date       0
dtype: int64
```

```
[ ] true_df.isna().sum()
```

```
title      0
text       0
subject    0
date       0
dtype: int64
```

5. We drop the columns that aren't relevant for fake news detection. These columns have no effect on determining whether the news is fake or true.

Dropping the unrequired columns

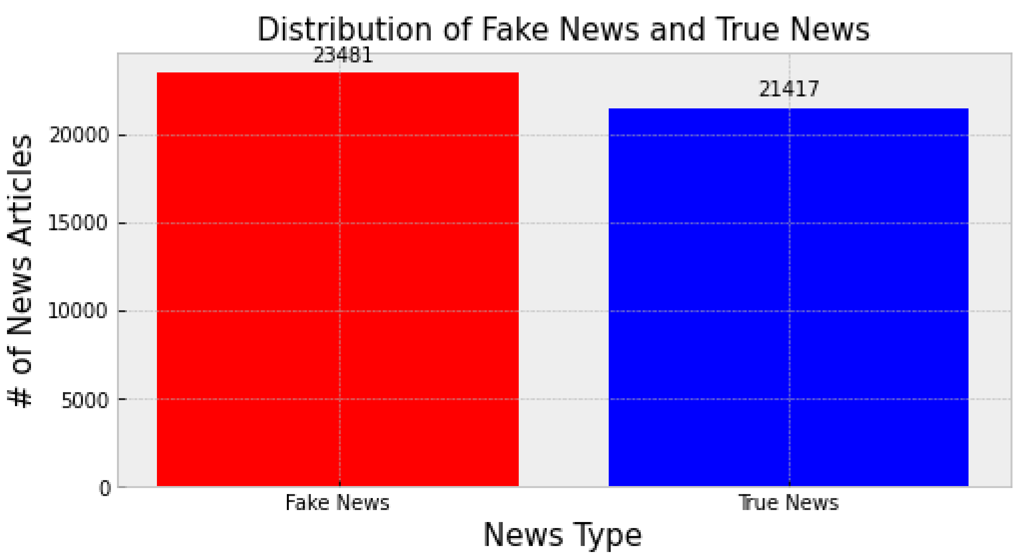
```
fake_df.drop(['subject','date'],axis=1,inplace=True)
```

```
[ ] true_df.drop(['subject','date'],axis=1,inplace=True)
```

6. Then we check the distribution of fake news and true news by plotting a bar plot. We see that the bar for fake news is higher since it has more records than true news, but the distribution is perfect to train our model as both the datasets have records in the range of 21-23k.

Checking the distribution of fake news vs true news

```
[ ] plt.figure(figsize=(8, 4))
    plt.bar('Fake News', len(fake_df), color='red')
    plt.bar('True News', len(true_df), color='blue')
    plt.title('Distribution of Fake News and True News', size=15)
    plt.xlabel('News Type', size=15)
    plt.ylabel('# of News Articles', size=15)
    plt.annotate(len(fake_df), # this is the text
                 (0.01,23000), # these are the coordinates to position the label
                 textcoords="offset points", # how to position the text
                 xytext=(0,10), # distance from text to points (x,y)
                 ha='center')
    plt.annotate(len(true_df), # this is the text
                 (1,21000), # these are the coordinates to position the label
                 textcoords="offset points", # how to position the text
                 xytext=(0,10), # distance from text to points (x,y)
                 ha='center')
    plt.show()
```



7. To simplify the data, we concatenate the title and text columns into news column in both the datasets and drop the former two. We create a new column ‘label’ which has values of 0-fake and 1-true.

Concatenating the title and text columns

```
[ ] fake_df['news'] = fake_df['title'] + fake_df['text']
    fake_df['label'] = 0
    fake_df.drop(['title','text'], axis=1, inplace=True)
```

```
[ ] true_df['news'] = true_df['title'] + true_df['text']
    true_df['label'] = 1
    true_df.drop(['title','text'], axis=1, inplace=True)
```

```
fake_df.sample(2)
```

	news	label
7059	WATCH: New Yorkers Send Donald Trump A POWERF...	0
21296	LIBERAL LUNACY: A Real Tom Turkey You'll Get A...	0

```
[ ] true_df.sample(2)
```

	news	label
11703	Turkey says U.S. isolated on Jerusalem, issuin...	1
8387	Tech firms' encryption foe struggles for U.S. ...	1

8. We visualize the news present in the True news dataset by creating a Wordcloud to highlight the popular words and phrases based on frequency and relevance.

Visualizing the news using wordcloud

```
[ ]  stopwords = set(STOPWORDS)

     words_li_true = list(true_df['news'])
     string_of_words_true = " ".join(words_li_true)

     wordcloud = WordCloud(width = 800, height = 800,
                     background_color ='white',
                     stopwords = stopwords,
                     min_font_size = 10).generate(string_of_words_true)

     # plot the WordCloud image
     plt.figure(figsize = (8, 8), facecolor = None)
     plt.imshow(wordcloud)
     plt.axis("off")
     plt.tight_layout(pad = 0)

     plt.show()
```

9. Similarly, to visualize the text or news present in fake news dataset, we create another word cloud.

```
[ ]  words_li_fake = list(fake_df['news'])
     string_of_words_fake = " ".join(words_li_fake)

     wordcloud = WordCloud(width = 800, height = 800,
                     background_color ='white',
                     stopwords = stopwords,
                     min_font_size = 10).generate(string_of_words_fake)

     # plot the WordCloud image
     plt.figure(figsize = (8, 8), facecolor = None)
     plt.imshow(wordcloud)
     plt.axis("off")
     plt.tight_layout(pad = 0)

     plt.show()
```

10. In order to build, train and test our models, we need to concatenate the datasets into a single dataset. We concatenate the datasets in the new dataset.

Concatenating the true and fake news datasets

```
[ ] df = pd.concat([fake_df, true_df], ignore_index=True, sort=False)
```

```
df.sample(5)
```

	news	label
33022	Obama: US, Nordic nations agree sanctions agai...	1
14119	WATCH: FRATERNITY BROTHERS BUILD “Make America...	0
19795	ROSEANNE BARR PAID HIGH PRICE For Crossing Hil...	0
27889	Hillary Clinton calls for U.S. to bomb Syrian ...	1
28310	Puerto Rico governor aims to pare cuts at publ...	1

11. In order to preprocess the news text, we use NLP, where we first tokenize the text and then remove stop words, after which we lemmatize the text.

Using NLP to pre-process the news text

```
stop_words = nltk.corpus.stopwords.words('english')
```

\+ Code \+ Text

```
[ ] lemmatizer=WordNetLemmatizer()
    for index,row in df.iterrows():
        filter_sentence = ''

        sentence = row['news']
        sentence = re.sub(r'[^\w\s]','',sentence) #cleaning

        words = nltk.word_tokenize(sentence) #tokenization

        words = [w for w in words if not w in stop_words]  #stopwords removal

        for word in words:
            filter_sentence = filter_sentence + ' ' + str(lemmatizer.lemmatize(word)).lower() #try with stemming

        df.loc[index,'news'] = filter_sentence
```

```
[ ] df.sample(5)
```

	news	label
36345	man palestinian flag smash jewish restaurant ...	1
13520	she grew up believing blacks could only suppo...	0
9618	did hillary clinton really break her toe vide...	0
30066	obama sign defense spending bill criticizes g...	1
44392	fbi say witness us probe malaysias 1mdb fear ...	1

After that we use count vectorizer to transform our data from a collection of text documents to a matrix of token counts. We then use tf-idf vectorizer to convert the collection of raw documents to a matrix of TF-IDF features.

```
count_vectorizer = CountVectorizer()
count_vectorizer.fit_transform(df['news'])
freq_term_matrix = count_vectorizer.transform(df['news'])
tfidf = TfidfTransformer(norm="l2")
tfidf.fit(freq_term_matrix)
tf_idf_matrix = tfidf.fit_transform(freq_term_matrix)
```

12. Now that we have pre-processed our data, we split the data into testing and training data using train_test_split.

Splitting the dataset into test and train

```
[ ] X_train, X_test, y_train, y_test = train_test_split(tf_idf_matrix, df['label'], random_state=0)
```

I. Logistic Regression

1. We create our logistic regression model and fit our training data to it.

Logistic Regression

```
[ ] logistic_regression= LogisticRegression()
    logistic_regression.fit(X_train,y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

2. We then predict using our testing data. We use our predictions and testing labels to calculate the metrics - accuracy, precision, F1 score and recall. We get Accuracy - 98.80%, Precision- 98.69%, F1 Score- 98.74% and Recall- 98.78%.

```
[ ] predictions_lr=logistic_regression.predict(X_test)

    print("LOGISTIC REGRESSION: PERFORMANCE METRICS\n\n")

    accuracy_logistic = accuracy_score(y_test, predictions_lr)
    print("Accuracy: %.2f%%" % (accuracy_logistic * 100.0))

    precision_logistic = precision_score(y_test, predictions_lr, average=None)
    print("Precision: %.2f%%" % (precision_logistic[1] * 100.0))

    f1score_logistic= f1_score(y_test, predictions_lr, average=None)
    print("F1 Score: %.2f%%" % (f1score_logistic[1] * 100.0))

    recall_logistic = recall_score(y_test, predictions_lr, average=None)
    print("Recall: %.2f%%" % (recall_logistic[1] * 100.0))
```

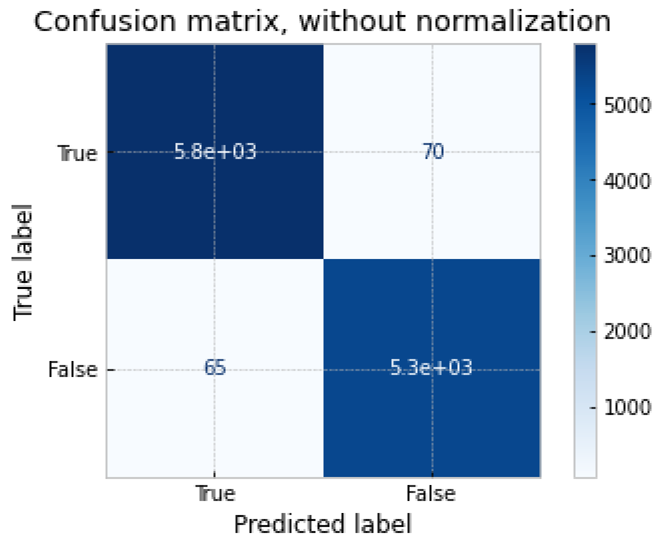
```
LOGISTIC REGRESSION: PERFORMANCE METRICS


Accuracy: 98.80%
Precision: 98.69%
F1 Score: 98.74%
Recall: 98.78%
```

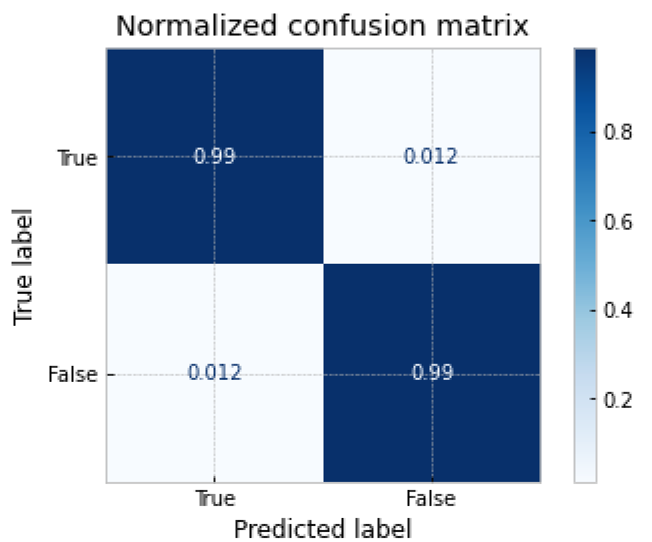
3. We plot a confusion matrix and a normalized confusion matrix.

+ Code + Text

```
class_names = ['True', 'False']

np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(logistic_regression, X_test, y_test,
                                 display_labels=class_names,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print()
    print(title)
    print(disp.confusion_matrix)

plt.show()
```

```
Confusion matrix, without normalization
[[5806   70]
 [  65 5284]]

Normalized confusion matrix
[[0.99 0.01]
 [0.01 0.99]]
```





II. ADA

1. We create our AdaBoost Classifier model and fit our training data to it.

```
[ ]  abc = AdaBoostClassifier(n_estimators=50,
                              learning_rate=1)
     # Train Adaboost Classifer
     ada_classifier = abc.fit(X_train, y_train)
```

2. We then predict using our testing data. We use our predictions and testing labels to calculate the metrics - accuracy, precision, F1 score and recall. We get Accuracy - 98.82%, Precision- 98.77%, F1 Score- 98.77% and Recall- 98.77%.

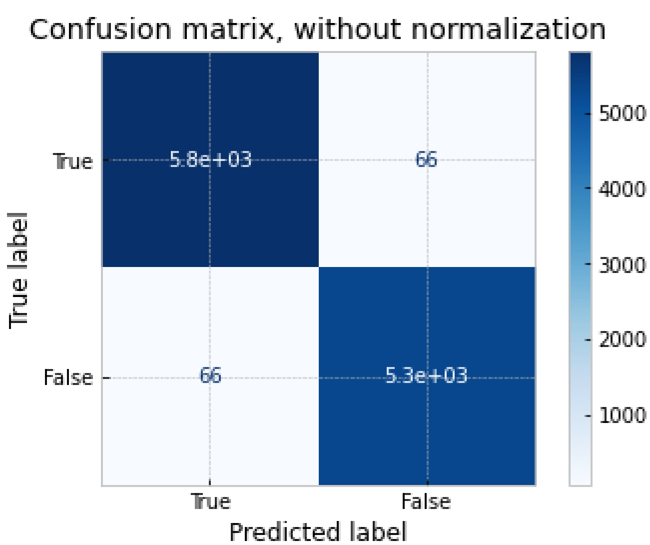
```
[ ] #Predict the response for test dataset
    predictions_ada = ada_classifier.predict(X_test)

    print("ADA BOOT CLASSIFIER: PERFORMANCE METRICS\n\n")

    accuracy_ada = accuracy_score(y_test, predictions_ada)
    print("Accuracy: %.2f%%" % (accuracy_ada * 100.0))

    precision_ada = precision_score(y_test, predictions_ada, average=None)
    print("Precision: %.2f%%" % (precision_ada[1] * 100.0))

    f1score_ada = f1_score(y_test, predictions_ada, average=None)
    print("F1 Score: %.2f%%" % (f1score_ada[1] * 100.0))

    recall_ada = recall_score(y_test, predictions_ada, average=None)
    print("Recall: %.2f%%" % (recall_ada[1] * 100.0))
```

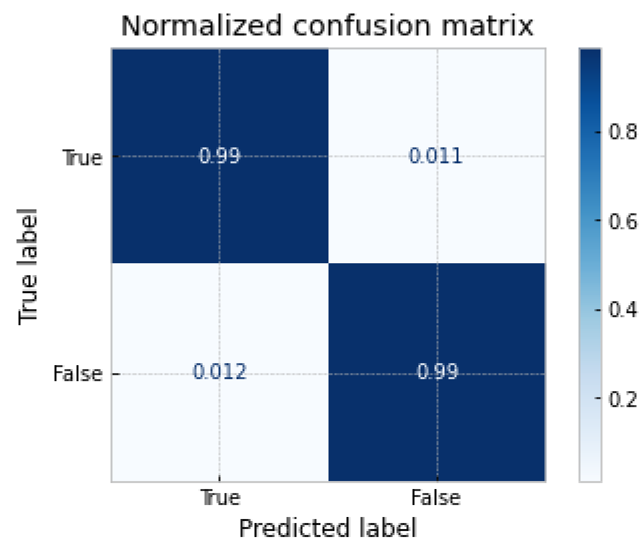
```
ADA BOOT CLASSIFIER: PERFORMANCE METRICS


Accuracy: 98.82%
Precision: 98.77%
F1 Score: 98.77%
Recall: 98.77%
```

3. We plot a confusion matrix and a normalized confusion matrix.

```python
class_names = ['True', 'False']

np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(ada_classifier, X_test, y_test,
                                 display_labels=class_names,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print()
    print(title)
    print(disp.confusion_matrix)

plt.show()
```

```
Confusion matrix, without normalization
[[5810   66]
 [  66 5283]]

Normalized confusion matrix
[[0.99 0.01]
 [0.01 0.99]]
```





III. PAC

1. We create our Passive Aggressive Classifier model and fit our training data to it.

```
[ ]  pac=PassiveAggressiveClassifier(max_iter=50)
     pac_classifier = pac.fit(X_train,y_train)
```

2. We then predict using our testing data. We use our predictions and testing labels to calculate the metrics - accuracy, precision, F1 score and recall. We get Accuracy - 99.54%, Precision- 99.46%, F1 Score- 99.51% and Recall- 99.57%.

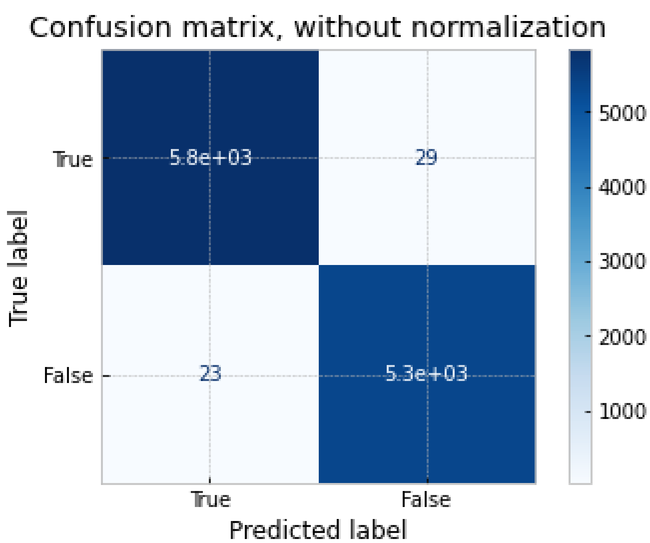
```
#Predict the response for test dataset
predictions_pac = pac_classifier.predict(X_test)

print("PASSIVE AGGRESSIVE CLASSIFIER: PERFORMANCE METRICS\n\n")

accuracy_pac = accuracy_score(y_test, predictions_pac)
print("Accuracy: %.2f%%" % (accuracy_pac * 100.0))

precision_pac = precision_score(y_test, predictions_pac, average=None)
print("Precision: %.2f%%" % (precision_pac[1] * 100.0))

f1score_pac = f1_score(y_test, predictions_pac, average=None)
print("F1 Score: %.2f%%" % (f1score_pac[1] * 100.0))

recall_pac = recall_score(y_test, predictions_pac, average=None)
print("Recall: %.2f%%" % (recall_pac[1] * 100.0))
```

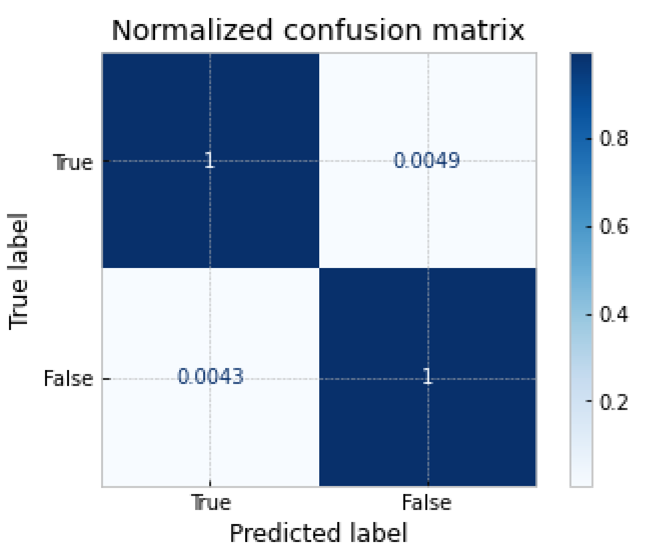
```
PASSIVE AGGRESSIVE CLASSIFIER: PERFORMANCE METRICS


Accuracy: 99.54%
Precision: 99.46%
F1 Score: 99.51%
Recall: 99.57%
```

3. We plot a confusion matrix and a normalized confusion matrix.

```
[ ] class_names = ['True', 'False']

    np.set_printoptions(precision=2)

    # Plot non-normalized confusion matrix
    titles_options = [("Confusion matrix, without normalization", None),
                      ("Normalized confusion matrix", 'true')]
    for title, normalize in titles_options:
        disp = plot_confusion_matrix(pac_classifier, X_test, y_test,
                                     display_labels=class_names,
                                     cmap=plt.cm.Blues,
                                     normalize=normalize)
        disp.ax_.set_title(title)

        print()
        print(title)
        print(disp.confusion_matrix)

    plt.show()
```

```
Confusion matrix, without normalization
[[5847   29]
 [  23 5326]]

Normalized confusion matrix
[[1. 0.]
 [0. 1.]]
```





IV. XGBoost

1. We create our XG Boost Classifier model and fit our training data to it.

```
xgb_classifier = XGBClassifier()

xgb_classifier.fit(X_train, y_train)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

2. We then predict using our testing data. We use our predictions and testing labels to calculate the metrics - accuracy, precision, F1 score and recall. We get Accuracy - 99.05%, Precision- 99.43%, F1 Score- 99.00% and Recall- 98.56%.

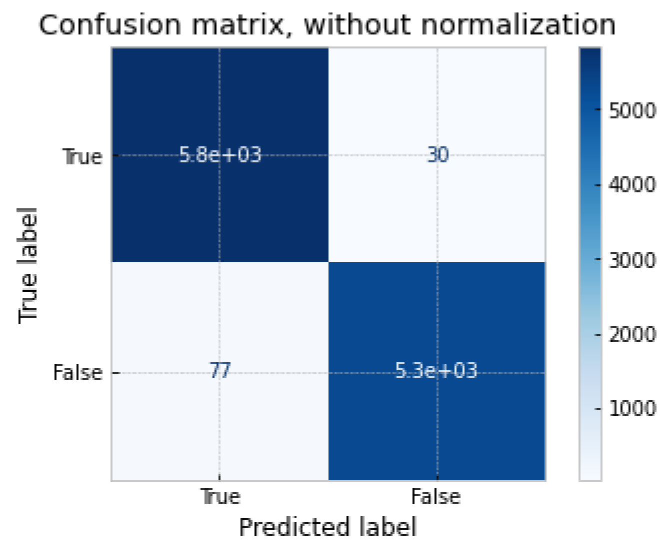
```python
predictions_xgb = xgb_classifier.predict(X_test)
predictions_xgbf = [round(value) for value in predictions_xgb]
# evaluate predictions

print("XG BOOST: PERFORMANCE METRICS\n\n")

accuracy_xgb = accuracy_score(y_test, predictions_xgbf)
print("Accuracy: %.2f%%" % (accuracy_xgb * 100.0))

precision_xgb = precision_score(y_test, predictions_xgbf, average=None)
print("Precision: %.2f%%" % (precision_xgb[1] * 100.0))

f1score_xgb = f1_score(y_test, predictions_xgbf, average=None)
print("F1 Score: %.2f%%" % (f1score_xgb[1] * 100.0))

recall_xgb = recall_score(y_test, predictions_xgbf, average=None)
print("Recall: %.2f%%" % (recall_xgb[1] * 100.0))
```

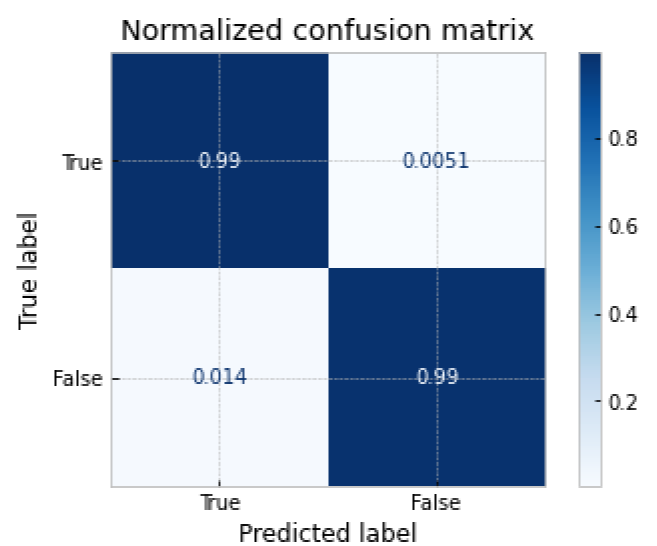
```
XG BOOST: PERFORMANCE METRICS


Accuracy: 99.05%
Precision: 99.43%
F1 Score: 99.00%
Recall: 98.56%
```

3. We plot a confusion matrix and a normalized confusion matrix.

```python
class_names = ['True', 'False']

np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(xgb_classifier, X_test, y_test,
                                 display_labels=class_names,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print()
    print(title)
    print(disp.confusion_matrix)

plt.show()
```

```
Confusion matrix, without normalization
[[5846   30]
 [  77 5272]]

Normalized confusion matrix
[[0.99 0.01]
 [0.01 0.99]]
```





V. Random Forest

1. We create our Random Forest Classifier model and fit our training data to it.

```
[ ] # Instantiate model with 30 decision trees
    rf = RandomForestClassifier(n_estimators = 30)
    # Train the model on training data
    rf.fit(X_train, y_train)
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=30,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

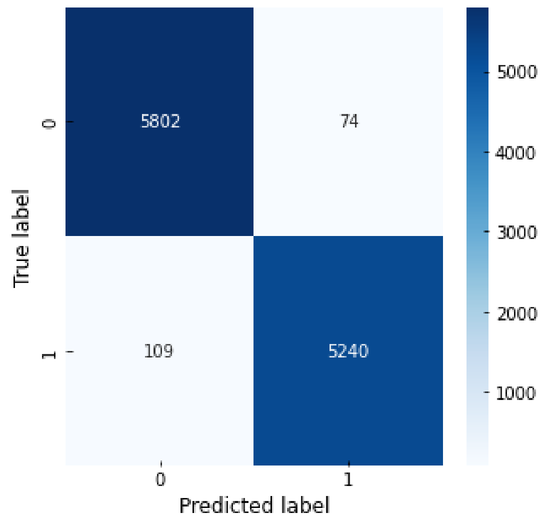
2. We then predict using our testing data. We use our predictions and testing labels to calculate the metrics - accuracy, precision, F1 score and recall. We get Accuracy - 98.37%, Precision- 98.61%, F1 Score- 98.28% and Recall- 97.96%.

```
[ ] # make predictions for test data
    y_pred_rf = rf.predict(X_test)
    predictions_rf = [round(value) for value in y_pred_rf]

    print("RANDOM FOREST: PERFORMANCE METRICS\n\n")

    accuracy_rf = accuracy_score(y_test, predictions_rf)
    print("Accuracy: %.2f%%" % (accuracy_rf * 100.0))

    precision_rf = precision_score(y_test, predictions_rf, average=None)
    print("Precision: %.2f%%" % (precision_rf[1] * 100.0))

    f1score_rf = f1_score(y_test, predictions_rf, average=None)
    print("F1 Score: %.2f%%" % (f1score_rf[1] * 100.0))

    recall_rf = recall_score(y_test, predictions_rf, average=None)
    print("Recall: %.2f%%" % (recall_rf[1] * 100.0))
```

```
RANDOM FOREST: PERFORMANCE METRICS


Accuracy: 98.37%
Precision: 98.61%
F1 Score: 98.28%
Recall: 97.96%
```

3. We plot a confusion matrix.

```
[ ] cm = confusion_matrix(y_test, predictions_rf)
    f, ax = plt.subplots(figsize = (5,5))
    sns.heatmap(cm, annot = True, fmt =".0f", ax=ax,cmap=plt.cm.Blues)
    plt.xlabel("Predicted label")
    plt.ylabel("True label")
    plt.show()
```



VI. Naive Bayes

1. We create our Naive Bayes Classifier model and fit our training data to it.

```
# fit the training dataset on the NB classifier
Naive = naive_bayes.MultinomialNB()
naive_classifier = Naive.fit(X_train,y_train)
```

2. We then predict using our testing data. We use our predictions and testing labels to calculate the metrics - accuracy, precision, F1 score and recall. We get Accuracy - 95.23%, Precision- 95.11%, F1 Score- 94.99% and Recall- 94.88%.

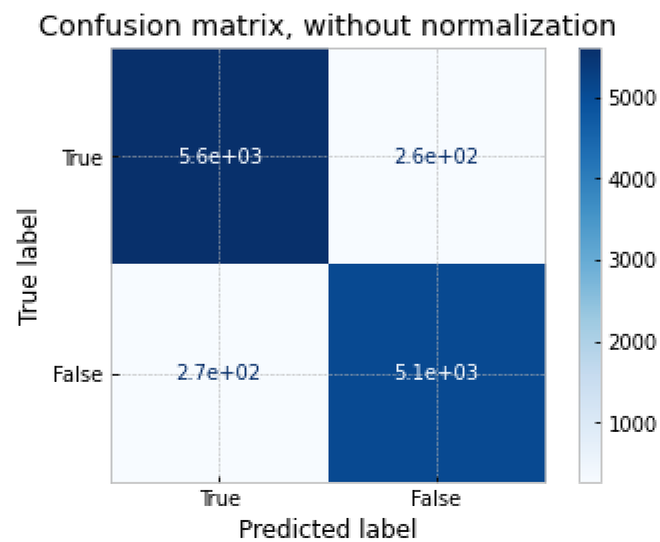
```python
# make predictions for test data
predictions_NB = Naive.predict(X_test)

print("NAIVE BAYES: PERFORMANCE METRICS\n\n")

accuracy_nb = accuracy_score(y_test, predictions_NB)
print("Accuracy: %.2f%%" % (accuracy_nb * 100.0))

precision_nb = precision_score(y_test, predictions_NB, average=None)
print("Precision: %.2f%%" % (precision_nb[1] * 100.0))

f1score_nb = f1_score(y_test, predictions_NB, average=None)
print("F1 Score: %.2f%%" % (f1score_nb[1] * 100.0))

recall_nb = recall_score(y_test, predictions_NB, average=None)
print("Recall: %.2f%%" % (recall_nb[1] * 100.0))
```

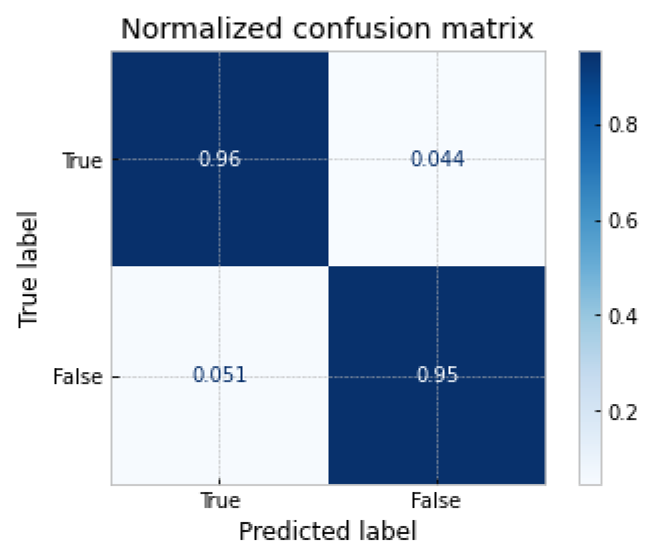
```
NAIVE BAYES: PERFORMANCE METRICS


Accuracy: 95.23%
Precision: 95.11%
F1 Score: 94.99%
Recall: 94.88%
```

3. We plot a confusion matrix and a normalized confusion matrix.

```python
class_names = ['True', 'False']

np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(naive_classifier, X_test, y_test,
                                 display_labels=class_names,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print()
    print(title)
    print(disp.confusion_matrix)

plt.show()
```

```
Confusion matrix, without normalization
[[5615  261]
 [ 274 5075]]

Normalized confusion matrix
[[0.96 0.04]
 [0.05 0.95]]
```





VII. Support Vector Machine (SVM)

1. We create our SVM Classifier model and fit our training data to it.

```
[ ] SVM = svm.SVC(C=1.0, kernel='linear', degree=3, gamma='auto')
    svm_classifier = SVM.fit(X_train,y_train)
```

2. We then predict using our testing data. We use our predictions and testing labels to calculate the metrics - accuracy, precision, F1 score

and recall. We get Accuracy - 99.48%, Precision- 99.33%, F1 Score- 99.46% and Recall- 99.59%

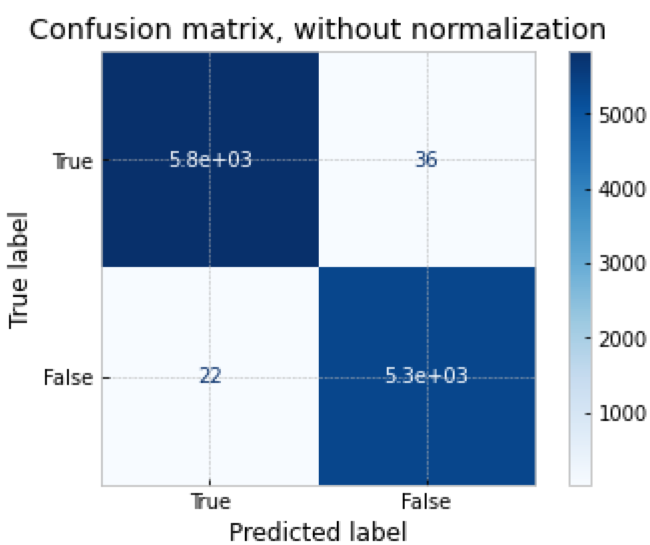
```
[ ] # make predictions for test data
    predictions_SVM = SVM.predict(X_test)

    print("SUPPORT VECTOR MACHINES: PERFORMANCE METRICS\n\n")

    accuracy_svm = accuracy_score(y_test, predictions_SVM)
    print("Accuracy: %.2f%%" % (accuracy_svm * 100.0))

    precision_svm = precision_score(y_test, predictions_SVM, average=None)
    print("Precision: %.2f%%" % (precision_svm[1] * 100.0))

    f1score_svm = f1_score(y_test, predictions_SVM, average=None)
    print("F1 Score: %.2f%%" % (f1score_svm[1] * 100.0))

    recall_svm = recall_score(y_test, predictions_SVM, average=None)
    print("Recall: %.2f%%" % (recall_svm[1] * 100.0))
```

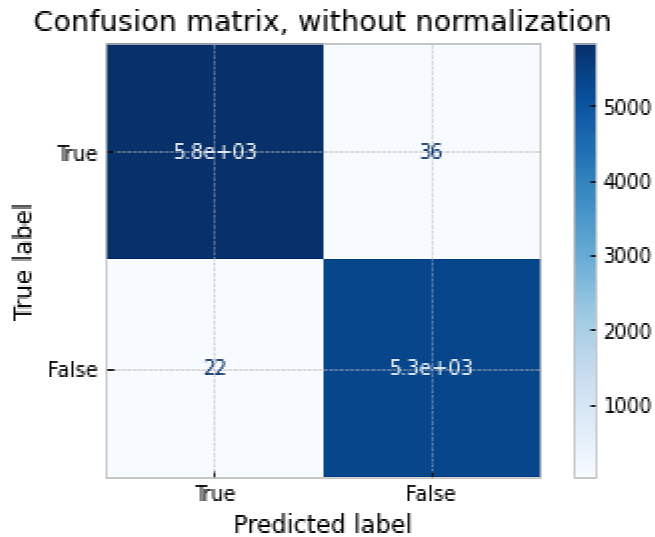
```
SUPPORT VECTOR MACHINES: PERFORMANCE METRICS


Accuracy: 99.48%
Precision: 99.33%
F1 Score: 99.46%
Recall: 99.59%
```

3. We plot a confusion matrix and a normalized confusion matrix.

```
[ ] class_names = ['True', 'False']

    np.set_printoptions(precision=2)

    # Plot non-normalized confusion matrix
    titles_options = [("Confusion matrix, without normalization", None),
                      ("Normalized confusion matrix", 'true')]
    for title, normalize in titles_options:
        disp = plot_confusion_matrix(svm_classifier, X_test, y_test,
                                     display_labels=class_names,
                                     cmap=plt.cm.Blues,
                                     normalize=normalize)
        disp.ax_.set_title(title)

        print(title)
        print(disp.confusion_matrix)

    plt.show()
```

```
Confusion matrix, without normalization
[[5840   36]
 [  22 5327]]
Normalized confusion matrix
[[0.99 0.01]
 [0.   1.  ]]
```





VIII. Decision Tree

1. We create our Decision Tree Classifier model and fit our training data to it.

```
[ ]  dt_clf = DecisionTreeClassifier()

     dt_clf = dt_clf.fit(X_train,y_train)
```

2. We then predict using our testing data. We use our predictions and testing labels to calculate the metrics - accuracy, precision, F1 score and recall. We get Accuracy - 98.67%, Precision- 98.73%, F1 Score- 98.61% and Recall- 98.49%

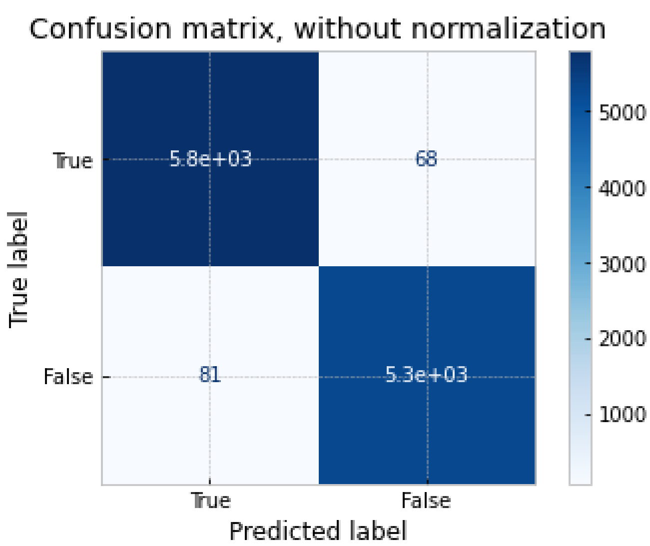
```python
# make predictions for test data
predictions_dt = dt_clf.predict(X_test)

print("DECISION TREE: PERFORMANCE METRICS\n\n")

accuracy_dt = accuracy_score(y_test, predictions_dt)
print("Accuracy: %.2f%%" % (accuracy_dt * 100.0))

precision_dt = precision_score(y_test, predictions_dt, average=None)
print("Precision: %.2f%%" % (precision_dt[1] * 100.0))

f1score_dt = f1_score(y_test, predictions_dt, average=None)
print("F1 Score: %.2f%%" % (f1score_dt[1] * 100.0))

recall_dt = recall_score(y_test, predictions_dt, average=None)
print("Recall: %.2f%%" % (recall_dt[1] * 100.0))
```

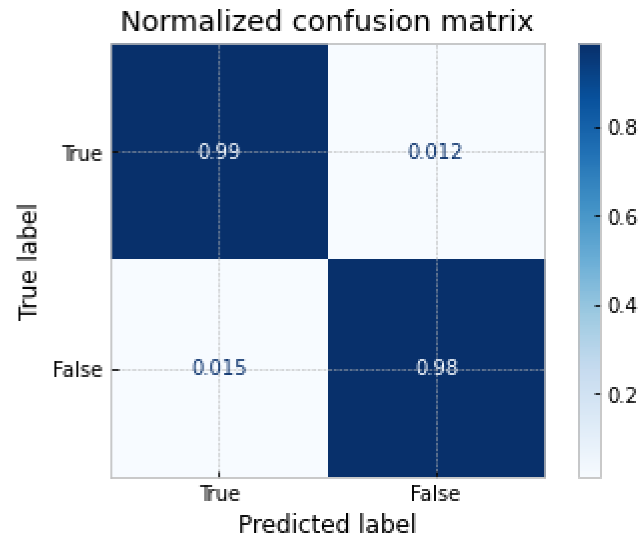
```
DECISION TREE: PERFORMANCE METRICS


Accuracy: 98.67%
Precision: 98.73%
F1 Score: 98.61%
Recall: 98.49%
```

3. We plot a confusion matrix and a normalized confusion matrix.

```
[ ] class_names = ['True', 'False']

    np.set_printoptions(precision=2)

    # Plot non-normalized confusion matrix
    titles_options = [("Confusion matrix, without normalization", None),
                      ("Normalized confusion matrix", 'true')]
    for title, normalize in titles_options:
        disp = plot_confusion_matrix(dt_clf, X_test, y_test,
                                     display_labels=class_names,
                                     cmap=plt.cm.Blues,
                                     normalize=normalize)
        disp.ax_.set_title(title)
        print()
        print(title)
        print(disp.confusion_matrix)

    plt.show()
```

```
Confusion matrix, without normalization
[[5808   68]
 [  81 5268]]

Normalized confusion matrix
[[0.99 0.01]
 [0.02 0.98]]
```





VIII. RNN

1. For our RNN model, we first preprocess the dataset news by normalizing it by removing non-words and extra spaces

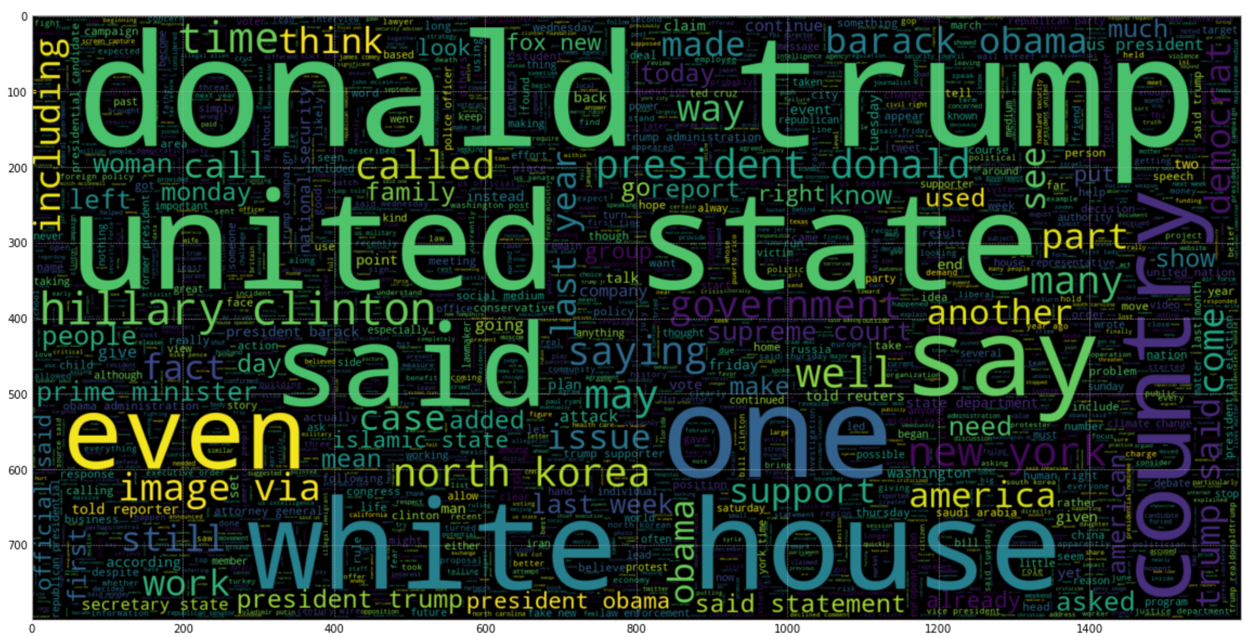
```
[ ] #normalizing the textual data
    import re

    def normalize(data):
        normalized = []
        for i in data:
            i = i.lower()
            # get rid of urls
            i = re.sub('https?://\S+|www\.\S+', '', i)
            # get rid of non words and extra spaces
            i = re.sub('\\W', ' ', i)
            i = re.sub('\n', '', i)
            i = re.sub(' +', ' ', i)
            i = re.sub('^ ', '', i)
            i = re.sub(' $', '', i)
            normalized.append(i)
        return normalized

    df['news'] = normalize(df['news'])

    #after normalizing
    df.sample(5)
```

	news	label
13297	transparent hillary clinton asked about terror...	0
6604	this university will punish you for being rape...	0
41846	rwanda charge critic president inciting insurr...	1
39160	bolstered libyan coast guard intercept packed ...	1
2957	trump stages photo of himself writing his own ...	0

2. We then create a Wordcloud to highlight the popular words and phrases based on frequency and relevance.

```
[ ] plt.figure(figsize = (20,20))
    wc = WordCloud(max_words = 3000 , width = 1600 , height = 800 , stopwords = STOPWORDS).generate(" ".join(df.news))
    plt.imshow(wc , interpolation = 'bilinear')
```

```
<matplotlib.image.AxesImage at 0x7f8688b05610>
```



3. After that we divide the dataset features and target into testing and training data.

```
feature = df['news']
target = df['label']

x_train_rnn, x_test_rnn, y_train_rnn, y_test_rnn = train_test_split(feature, target, test_size=0.20, random_state=18)
```

```
tokenizer = Tokenizer(num_words=10000)
tokenizer.fit_on_texts(x_train_rnn)
```

```
x_train_rnn = tokenizer.texts_to_sequences(x_train_rnn)
x_test_rnn = tokenizer.texts_to_sequences(x_test_rnn)
```

```
x_train_rnn = tf.keras.preprocessing.sequence.pad_sequences(x_train_rnn, padding='post', maxlen=256)
x_test_rnn = tf.keras.preprocessing.sequence.pad_sequences(x_test_rnn, padding='post', maxlen=256)
```

4. Then we build our RNN sequential model and add the layers to it

```
model_rnn = tf.keras.Sequential([
    tf.keras.layers.Embedding(10000, 32),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(64,  return_sequences=True)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(16)),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(1)
])


model_rnn.summary()
```

5. This is our model summary:

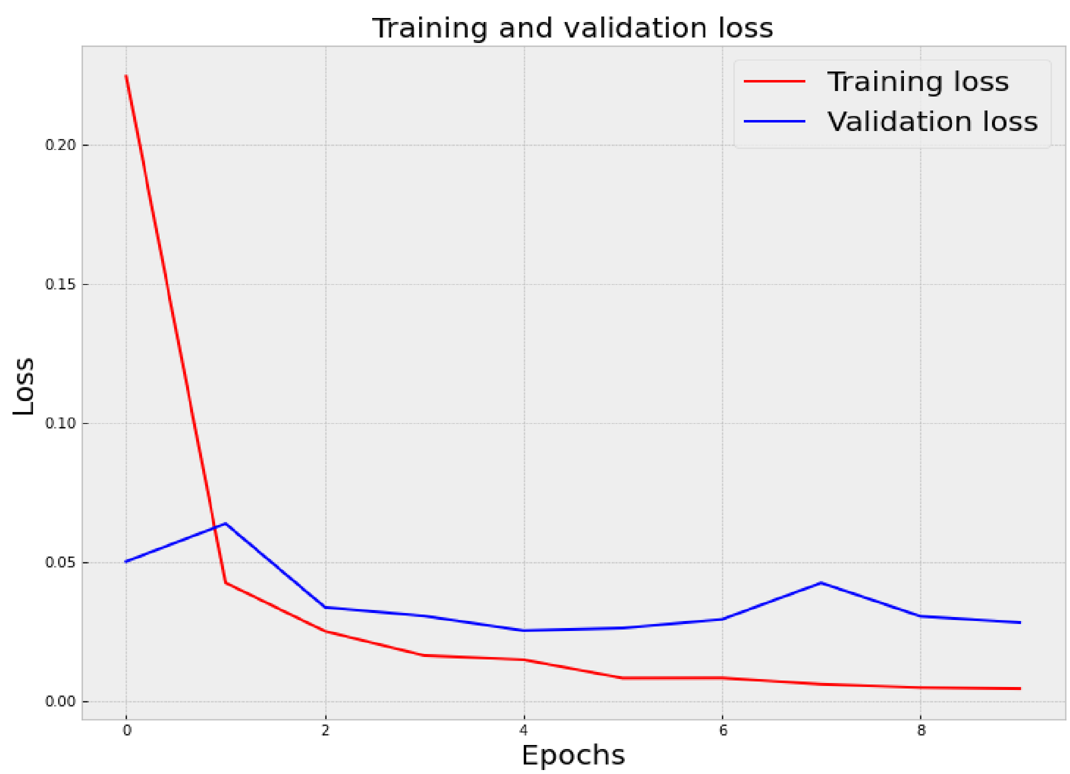
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, None, 32)          320000
_________________________________________________________________
bidirectional (Bidirectional (None, None, 128)         49664
_________________________________________________________________
bidirectional_1 (Bidirection (None, 32)                18560
_________________________________________________________________
dense (Dense)                (None, 64)                2112
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 65
=================================================================
Total params: 390,401
Trainable params: 390,401
Non-trainable params: 0
_________________________________________________________________
```

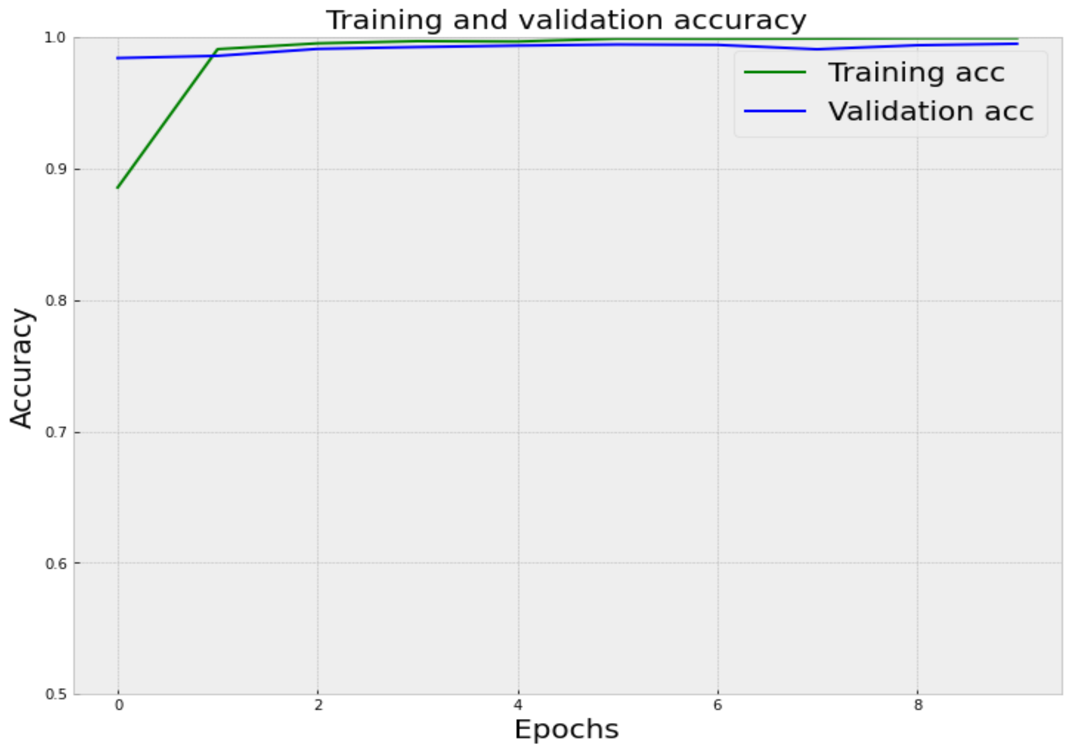
6. We compile our RNN model and fit the training data to it for 10 epochs. We see that with every epoch, the loss decreases and the accuracy increases. At the 10th epoch, we get a validation accuracy of 99.50% and the validation loss is 0.028, whereas the loss is of 0.0044 and accuracy is 99.93%

```
[ ] model_rnn.compile(loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
                  optimizer=tf.keras.optimizers.Adam(1e-4),
                  metrics=['accuracy'])

    history = model_rnn.fit(x_train_rnn, y_train_rnn, epochs=10,validation_split=0.1, batch_size=30, shuffle=True,)

    Epoch 1/10
    1078/1078 [==============================] - 470s 430ms/step - loss: 0.2243 - accuracy: 0.8856 - val_loss: 0.0501 - val_accuracy: 0.9841
    Epoch 2/10
    1078/1078 [==============================] - 471s 437ms/step - loss: 0.0424 - accuracy: 0.9909 - val_loss: 0.0637 - val_accuracy: 0.9858
    Epoch 3/10
    1078/1078 [==============================] - 470s 436ms/step - loss: 0.0251 - accuracy: 0.9953 - val_loss: 0.0337 - val_accuracy: 0.9911
    Epoch 4/10
    1078/1078 [==============================] - 470s 436ms/step - loss: 0.0163 - accuracy: 0.9970 - val_loss: 0.0306 - val_accuracy: 0.9925
    Epoch 5/10
    1078/1078 [==============================] - 468s 434ms/step - loss: 0.0149 - accuracy: 0.9967 - val_loss: 0.0253 - val_accuracy: 0.9936
    Epoch 6/10
    1078/1078 [==============================] - 472s 438ms/step - loss: 0.0082 - accuracy: 0.9989 - val_loss: 0.0262 - val_accuracy: 0.9944
    Epoch 7/10
    1078/1078 [==============================] - 473s 439ms/step - loss: 0.0083 - accuracy: 0.9988 - val_loss: 0.0293 - val_accuracy: 0.9942
    Epoch 8/10
    1078/1078 [==============================] - 472s 438ms/step - loss: 0.0060 - accuracy: 0.9990 - val_loss: 0.0424 - val_accuracy: 0.9908
    Epoch 9/10
    1078/1078 [==============================] - 474s 440ms/step - loss: 0.0048 - accuracy: 0.9993 - val_loss: 0.0304 - val_accuracy: 0.9939
    Epoch 10/10
    1078/1078 [==============================] - 479s 444ms/step - loss: 0.0044 - accuracy: 0.9993 - val_loss: 0.0282 - val_accuracy: 0.9950
```

7. We then use the model history to plot the training loss and accuracy:

```
[ ] history_dict = history.history

    acc = history_dict['accuracy']
    val_acc = history_dict['val_accuracy']
    loss = history_dict['loss']
    val_loss = history_dict['val_loss']
    epochs = history.epoch

    plt.figure(figsize=(12,9))
    plt.plot(epochs, loss, 'r', label='Training loss')
    plt.plot(epochs, val_loss, 'b', label='Validation loss')
    plt.title('Training and validation loss', size=20)
    plt.xlabel('Epochs', size=20)
    plt.ylabel('Loss', size=20)
    plt.legend(prop={'size': 20})
    plt.show()

    plt.figure(figsize=(12,9))
    plt.plot(epochs, acc, 'g', label='Training acc')
    plt.plot(epochs, val_acc, 'b', label='Validation acc')
    plt.title('Training and validation accuracy', size=20)
    plt.xlabel('Epochs', size=20)
    plt.ylabel('Accuracy', size=20)
    plt.legend(prop={'size': 20})
    plt.ylim((0.5,1))
    plt.show()
```





8. We evaluate the model with the testing data and the loss turns out to be 2.84% and an accuracy of 99.387%

```
[ ] model_rnn.evaluate(x_test_rnn, y_test_rnn)

281/281 [==============================] - 26s 91ms/step - loss: 0.0285 - accuracy: 0.9939
[0.028498206287622452, 0.99387526512146]
```

9. We then calculate other performance metrics. The accuracy as mentioned earlier is 99.39%, the precision is 99.35%, the f1 score is 99.36% and the recall is 99.37%.

```python
pred = model_rnn.predict(x_test_rnn)

binary_predictions = []

for i in pred:
    if i >= 0.5:
        binary_predictions.append(1)
    else:
        binary_predictions.append(0)
```

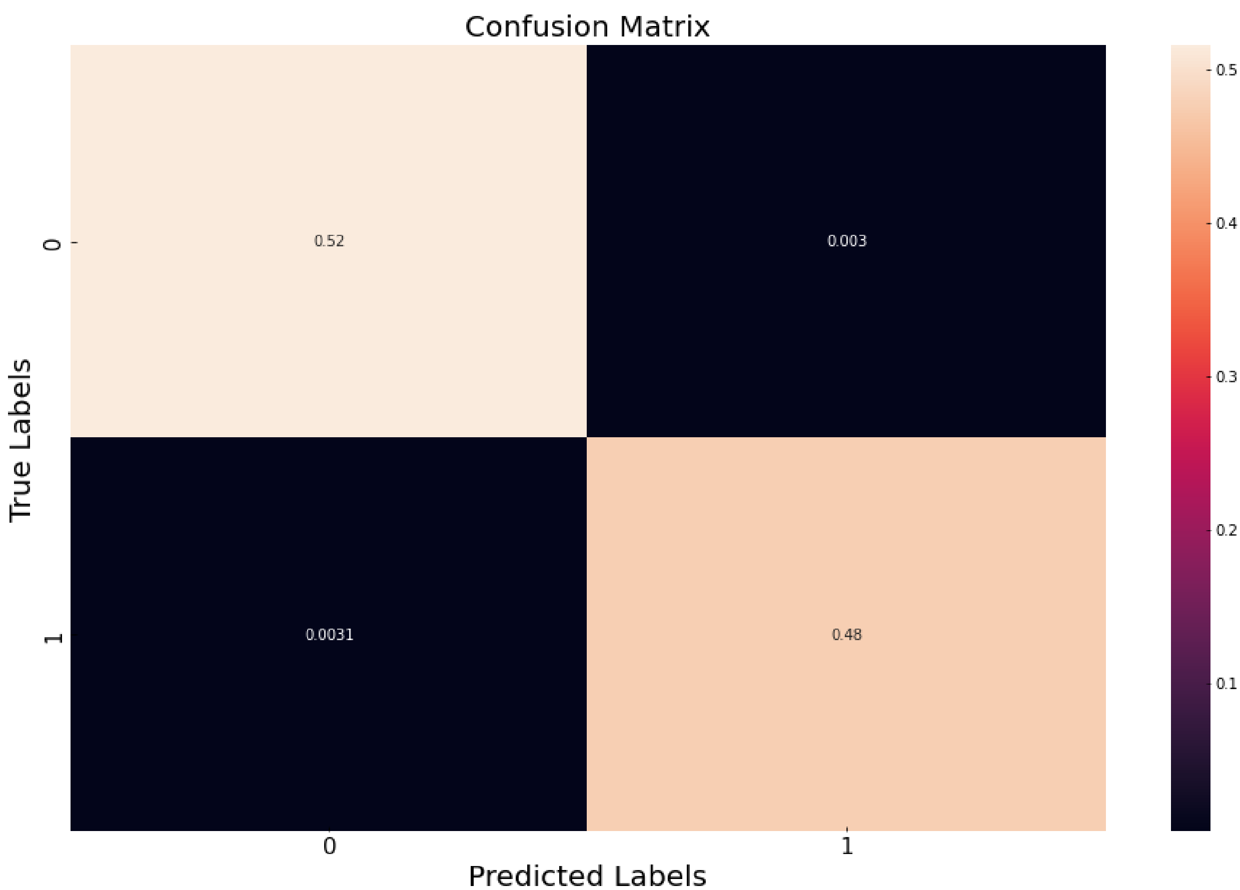
```python
print("RNN: PERFORMANCE METRICS\n\n")

accuracy_rnn = accuracy_score(y_test_rnn, binary_predictions)
print("Accuracy: %.2f%%" % (accuracy_rnn * 100.0))

precision_rnn = precision_score(y_test_rnn, binary_predictions, average=None)
print("Precision: %.2f%%" % (precision_rnn[1] * 100.0))

f1score_rnn = f1_score(y_test_rnn, binary_predictions, average=None)
print("F1 Score: %.2f%%" % (f1score_rnn[1] * 100.0))

recall_rnn = recall_score(y_test_rnn, binary_predictions, average=None)
print("Recall: %.2f%%" % (recall_rnn[1] * 100.0))
```

```
RNN: PERFORMANCE METRICS


Accuracy: 99.24%
Precision: 99.49%
F1 Score: 99.21%
Recall: 98.93%
```

10. We also plot a confusion matrix to see how well has our model classified the records.

```python
matrix = confusion_matrix(binary_predictions, y_test_rnn, normalize='all')
plt.figure(figsize=(16, 10))
ax= plt.subplot()
sns.heatmap(matrix, annot=True, ax = ax)

# labels, title and ticks
ax.set_xlabel('Predicted Labels', size=20)
ax.set_ylabel('True Labels', size=20)
ax.set_title('Confusion Matrix', size=20)
ax.xaxis.set_ticklabels([0,1], size=15)
ax.yaxis.set_ticklabels([0,1], size=15)
```

```
[Text(0, 0.5, '0'), Text(0, 1.5, '1')]
```



X. Comparing all the Models

1. We create separate lists to store the performance metrics of each model and create a dataframe for it.

```
[ ] var_models = ['Logstic Regression', 'ADA', 'PAC', 'XGB','RF','Naive Bayes','SVM','DT','RNN']

    var_accuracy = [accuracy_logistic,accuracy_ada,accuracy_pac,accuracy_xgb,accuracy_rf,accuracy_nb,accuracy_svm,accuracy_dt,accuracy_rnn]
    var_precision = [precision_logistic[1],precision_ada[1],precision_pac[1],precision_xgb[1],precision_rf[1],precision_nb[1],precision_svm[1],precision_dt[1],prec
    var_f1score = [f1score_logistic[1],f1score_ada[1],f1score_pac[1],f1score_xgb[1],f1score_rf[1],f1score_nb[1],f1score_svm[1],f1score_dt[1],f1score_rnn[1]]
    var_recall = [recall_logistic[1],recall_ada[1],recall_pac[1],recall_xgb[1],recall_rf[1],recall_nb[1],recall_svm[1],recall_dt[1],recall_rnn[1]]
```

```
[ ]
    metrics = pd.DataFrame({'Models': var_models,'Accuracy': var_accuracy,'Precision': var_precision, 'F1 Score': var_f1score, 'Recall':var_recall})

    print("Table of Comparison:\n\n")
    metrics
```

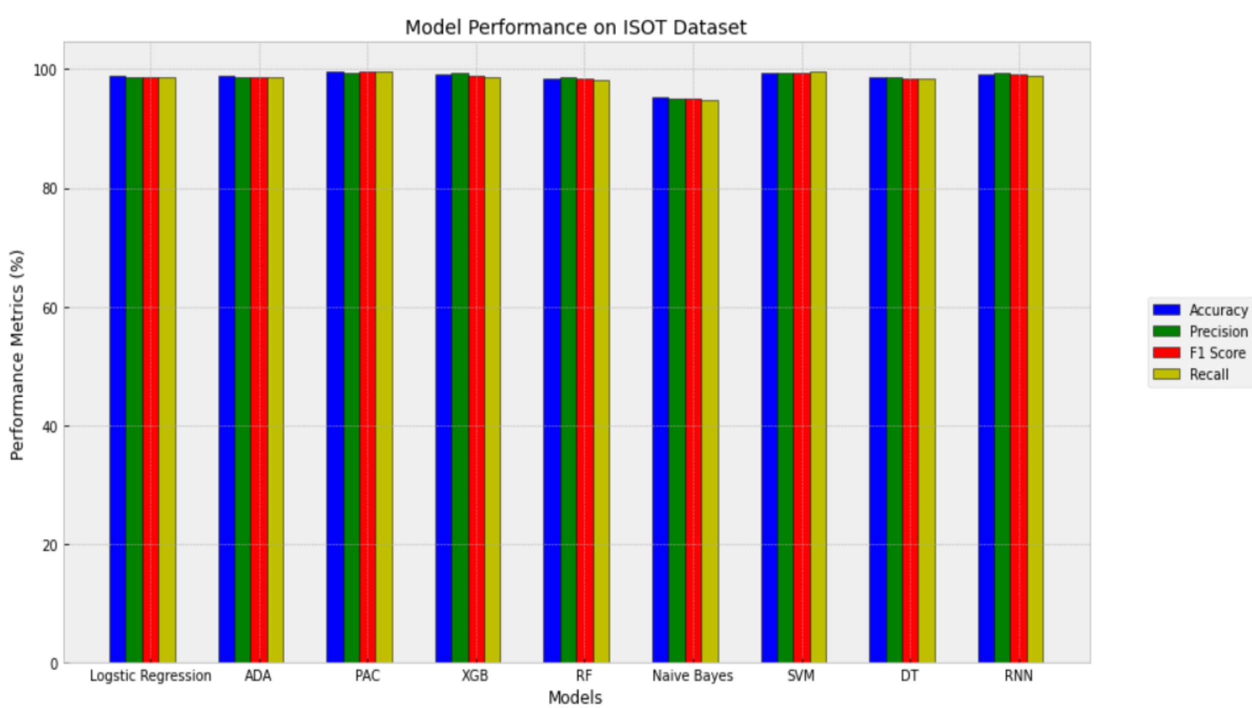
2. This is the dataframe that we have created which shows the models and their performance metrics.

```
Table of Comparison:
```

	Models	Accuracy	Precision	F1 Score	Recall
0	Logstic Regression	0.987973	0.986926	0.987387	0.987848
1	ADA	0.988241	0.987661	0.987661	0.987661
2	PAC	0.995367	0.994585	0.995142	0.995700
3	XGB	0.990468	0.994342	0.989954	0.985605
4	RF	0.983697	0.986075	0.982838	0.979622
5	Naive Bayes	0.952339	0.951087	0.949930	0.948775
6	SVM	0.994833	0.993287	0.994586	0.995887
7	DT	0.986726	0.987256	0.986055	0.984857
8	RNN	0.993875	0.993517	0.993632	0.993747

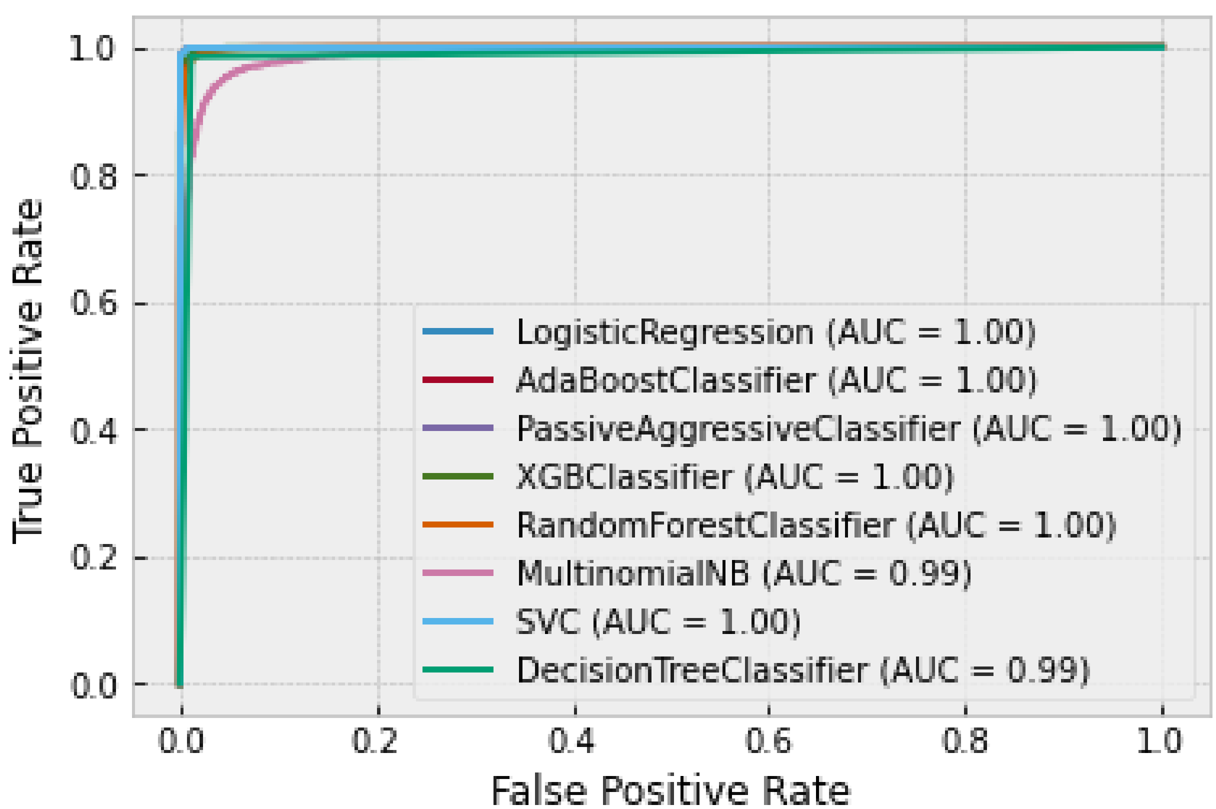
3. We plot a bar graph to compare the performance metrics of all the models on the ISOT dataset.

```
plt.figure(figsize=(14,8))
n= len(var_models)
r = np.arange(n)
width = 0.15

plt.bar(r, [i*100 for i in var_accuracy], color = 'b',
        width = width, edgecolor = 'black',
        label='Accuracy')
plt.bar(r + width, [i*100 for i in var_precision], color = 'g',
        width = width, edgecolor = 'black',
        label='Precision')
plt.bar(r + width*2,  [i*100 for i in var_f1score], color = 'r',
        width = width, edgecolor = 'black',
        label='F1 Score')
plt.bar(r + width*3,  [i*100 for i in var_recall], color = 'y',
        width = width, edgecolor = 'black',
        label='Recall')

plt.xlabel("Models")
plt.ylabel("Performance Metrics (%)")
plt.title("Model Performance on ISOT Dataset")

plt.xticks(r + width*2,var_models)
plt.legend()

plt.show()
```



4. We also plot the ROC curve to better understand the performance of each model. We see that SVM is ideally the best classifier for our dataset.

```
#plotting the roc curve
plt.figure(figsize=(14,10))
disp = plot_roc_curve(logistic_regression,X_test,y_test)
plot_roc_curve(ada_classifier,X_test,y_test,ax=disp.ax_)
plot_roc_curve(pac_classifier,X_test,y_test,ax=disp.ax_)
plot_roc_curve(xgb_classifier,X_test,y_test,ax=disp.ax_)
plot_roc_curve(rf,X_test,y_test,ax=disp.ax_)
plot_roc_curve(naive_classifier,X_test,y_test,ax=disp.ax_)
plot_roc_curve(svm_classifier,X_test,y_test,ax=disp.ax_)
plot_roc_curve(dt_clf,X_test,y_test,ax=disp.ax_)
plt.show()
```



Outcome:

CO3: Comprehend radial-basis-function (RBF) networks and Kernel learning method work.

Conclusion: (Conclusion to be based on the objectives and outcomes achieved)

We downloaded the ISOT dataset from https://www.uvic.ca/ecs/ece/isot/datasets/index.php and uploaded it to our drive, and then loaded it and preprocessed it using various NLP algorithms like tokenization, stop words removal, lemmatization and stemming. We vectorized the text documents using count vectorizer and tf-idf vectorizer. After preprocessing, we split the data into testing and training and we built nine models using nine different classification algorithms and used the predictions to calculate the performance metrics. The details of each are given below:

Sr	Models	Accuracy	Precision	F1 Score	Recall
1	Logistic Regression	0.987973	0.986926	0.987387	0.987848
2	ADABoost Classifier	0.988241	0.987661	0.987661	0.987661
3	Passive Aggressive Classifier	0.995367	0.994585	0.995142	0.995700
4	XG Boost	0.990468	0.994342	0.989954	0.985605
5	Random Forest	0.983697	0.986075	0.982838	0.979622
6	Naive Bayes	0.952339	0.951087	0.949930	0.948775
7	SVM	0.994833	0.993287	0.994586	0.995887
8	Decision Tree	0.986726	0.987256	0.986055	0.984857
9	RNN	0.993875	0.993517	0.993632	0.993747

From the ROC curve and the bar plot which compares the performance of all the models, we conclude that the SVM (accuracy-99.48%, precision - 99.33%, f1 score-99.46%, recall-99.59%) is the best algorithm on our ISOT dataset for the task of fake news detection and classification.