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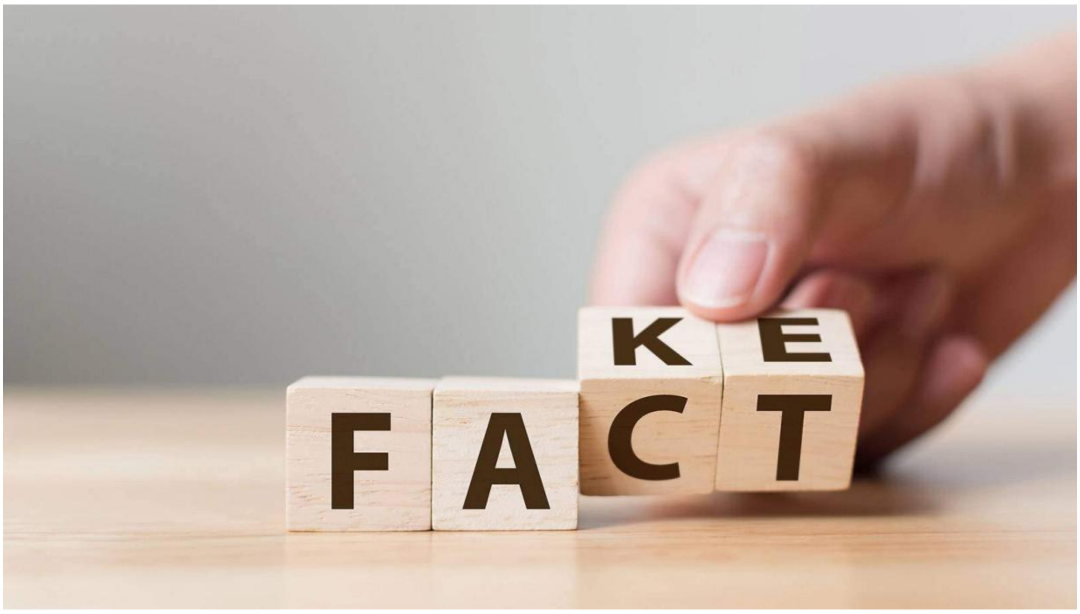
TEAM - 05

Fake News Detection Using NLP

Fake news detection using Natural Language Processing (NLP) is a crucial application of AI and NLP techniques to combat the spread of misinformation. In this example, I'll provide a simplified Python program that uses NLP and machine learning to classify news articles as either real or fake. Note that real-world applications of fake news detection are more complex and require large datasets and more sophisticated models.

Here's a step-by-step guide and a basic Python program:



Step 1: Import

```
import pandas as pd

import re

from nltk.corpus import stopwords

from nltk.tokenize import word_tokenize

from wordcloud import WordCloud

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
```

```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense
from sklearn.metrics import log_loss, roc_auc_score, confusion_matrix
import seaborn as sns
```

Step 2 : Import Dataset

```
true_data = pd.read_csv('/kaggle/input/fake-and-real-news-dataset/True.csv')
fake_data = pd.read_csv('/kaggle/input/fake-and-real-news-dataset/Fake.csv')
```

Step 3 : Adding Truth Value Labels

```
# Add labels and merge the data
fake_data['label'] = 'fake'
true_data['label'] = 'true'
merged_data = pd.concat([fake_data, true_data])
```

Step 4 : EDA

```
true_data.head()
fake_data.head()
merged_data =
merged_data.sample(frac=1).reset_index(drop=True)
merged_data.head()
merged_data.dtypes
```

Calculate label distribution

label_distribution = merged_data['label'].value_counts()

Extracting labels and counts for pie chart

labels = [f"{label} ({count})" for label, count in zip(label_distribution.index, label_distribution.values)]

Plotting the pie chart

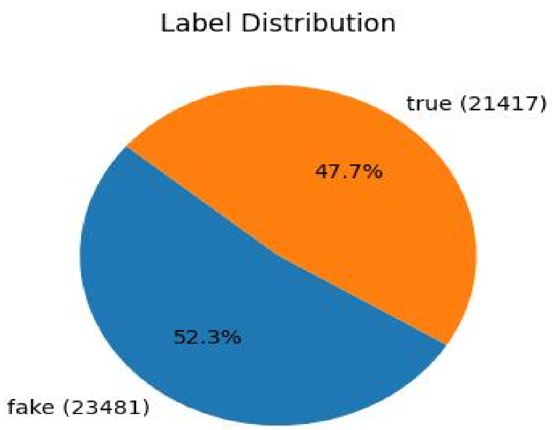
plt.figure(figsize=(4, 4))

plt.pie(label_distribution, labels=labels, autopct='%1.1f%%', startangle=140)

plt.title('Label Distribution')

plt.show()

<u>Output:</u>



Step 5 : Preprocessing the Text

def preprocess_text(text):

```
    # Convert text to lowercase
    text = text.lower()
    # Remove punctuations
    text = re.sub(r'[^\w\s]', '', text)
    # Tokenize the text
    words = word_tokenize(text)
    # Remove stopwords and words with length <= 2
    stop_words = set(stopwords.words('english'))
    words = [word for word in words if word not in stop_words and
len(word) > 2]
    # Remove repeated words
    words = list(dict.fromkeys(words))
    # Join the words back into text
    text = ' '.join(words)
      return text
```

```
merged_data['clean_text'] = merged_data['text'].apply(preprocess_text)
merged_data.clean_text
```

Output:

```
0        united nations reuters general assembly wednes...
1        james keefe released blockbuster undercover vi...
2        gina loudon went cnn today discuss fallacious ...
3                    must watch videohttpsyoutube5zjj2z4bu
4        washington reuters senate thursday passed legi...
                               ...
44893    senator john mccain got outed hypocrite damnin...
44894    washington reuters senate democratic leader ch...
44895    think like knowwatch susan rice insists leaked...
44896    donald trump recently came proposal new tax pl...
44897    paris reuters french president emmanuel macron...
Name: clean_text, Length: 44898, dtype: object
```

Distribution :

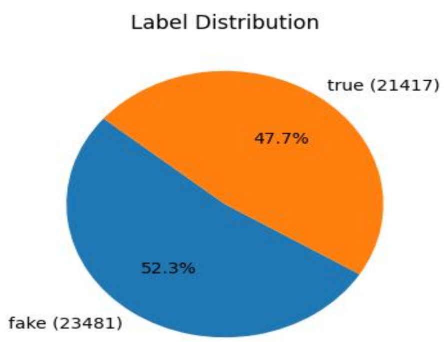
```
    # Calculate label distribution
```

```
label_distribution = merged_data['label'].value_counts()


# Extracting labels and counts for pie chart
labels = [f"{label} ({count})" for label, count in zip(label_distribution.index, label_distribution.values)]


# Plotting the pie chart
plt.figure(figsize=(4, 4))
plt.pie(label_distribution, labels=labels, autopct='%1.1f%%', startangle=140)
plt.title('Label Distribution')
plt.show()
```

<u>Output:</u>



Step 6 :Checking Fake Political News and Fake News Buzzwords

```
fake_politics_data = ' '.join(merged_data[(merged_data['subject'] == 'politics') & (merged_data['label'] == 'fake')]['clean_text'])
total_fake_news = ' '.join(merged_data[merged_data['label'] == 'fake']['clean_text'])
```

fake_politics_data[0:500]

Output:

James Keefe released blockbuster undercover video yesterday saying going commit acts terror trump supporters attend deploraball washington seen hereone organizers mike chernovich conservative author activist active twitter excerpt admit committing act domestic terrorism buy tickets overt criminal conspiracy definitely picked wrong group try terrorize jeff sessions gon attorney general new department justice thought dealing obama would let say people cares well charge anymore eric holder loretta.

total_fake_news[0:500]

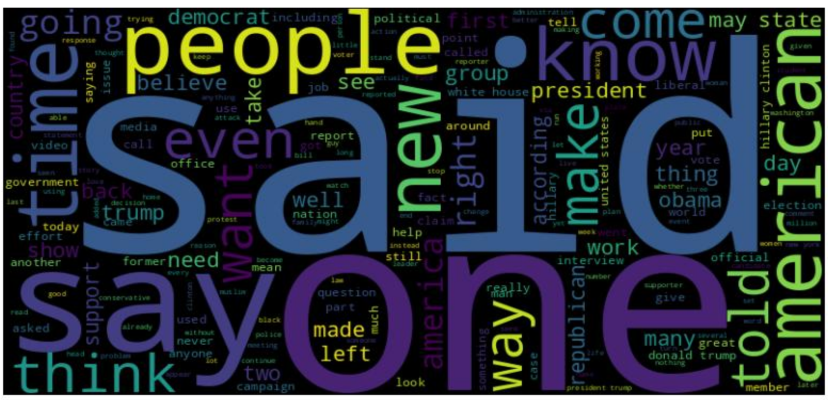
Output:

***James Keefe released blockbuster undercover video yesterday saying going commit acts ter
ror trump supporters attend deploraball washington seen hereone organizers mike chernov
ich conservative author activist active twitter excerpt admit committing act domestic terrori
sm buy tickets overt criminal conspiracy definitely picked wrong group try terrorize jeff ses
sions gon attorney general new department justice thought dealing obama would let say pe
ople cares well charge anymore eric holder loretta.***

```
wordcloud = WordCloud(width=800,
height=400).generate(fake_politics_data)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Fake Politics News')
plt.show()
```

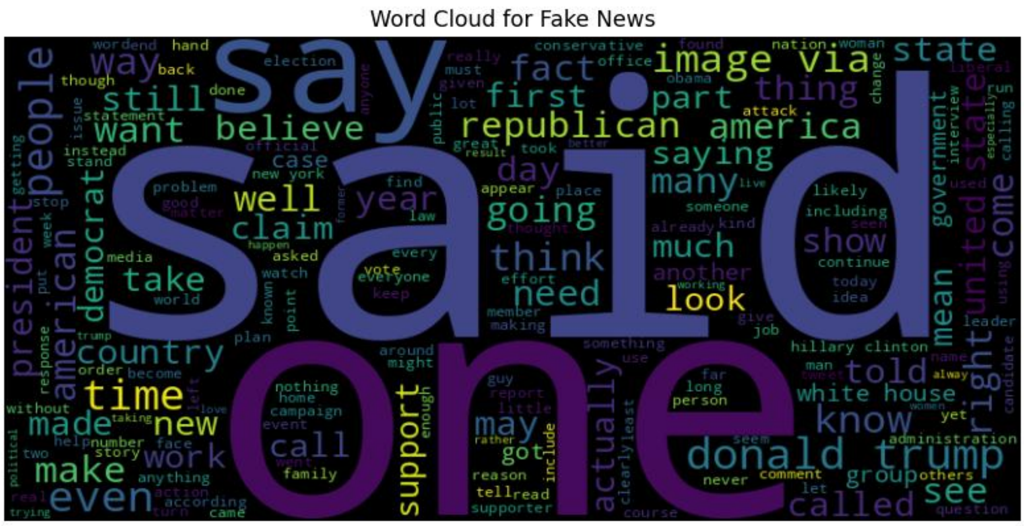
Output:

Word Cloud for Fake Politics News



```
wordcloud = WordCloud(width=800,
height=400).generate(total_fake_news)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Fake News')
plt.show()
```

<u>Output:</u>



Step 7 : Splitting the Dataset

```
X = merged_data['clean_text']
y = merged_data['label']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
```

Step 8: Performing Tokenization

```
# Tokenize text
tokenizer = Tokenizer()
tokenizer.fit_on_texts(X_train)
X_train_tokens = tokenizer.texts_to_sequences(X_train)
X_test_tokens = tokenizer.texts_to_sequences(X_test)

# print(f"Total tokens: {len(tokenizer.word_index)}")

# Calculate total tokens
total_tokens = sum([len(tokens) for tokens in X_train_tokens])
print("Total Tokens:", total_tokens)
```

Output:

Total Tokens: 5831432

```
# Apply post padding
maxlen = 20
X_train_pad = pad_sequences(X_train_tokens, maxlen=maxlen,
padding='post')
X_test_pad = pad_sequences(X_test_tokens, maxlen=maxlen,
padding='post')
```

Step 9 : RNN Model

```
# Build the RNN model
```

```
model = Sequential()
model.add(Embedding(input_dim=len(tokenizer.word_index) + 1, output_dim=4, input_length=maxlen))
model.add(SimpleRNN(units=128, return_sequences=True))
model.add(SimpleRNN(units=64, return_sequences=True))
model.add(SimpleRNN(units=32))
model.add(Dense(units=1, activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy', 'AUC'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 20, 4)             810784

 simple_rnn (SimpleRNN)      (None, 20, 128)           17024

 simple_rnn_1 (SimpleRNN)    (None, 20, 64)            12352

 simple_rnn_2 (SimpleRNN)    (None, 32)                3104

 dense (Dense)               (None, 1)                 33

=================================================================
Total params: 843,297
Trainable params: 843,297
Non-trainable params: 0
_________________________________________________________________
```

```
# Train the model
model.fit(X_train_pad, y_train.map({'fake': 1, 'true': 0}),  epochs=20, validation_data=(X_test_pad, y_test.map({'fake': 1, 'true': 0})))
```

Output:

Epoch 1/20
1123/1123 [==============================] - 29s 23ms/step - loss: 0.2698 - accuracy: 0.8684 - auc: 0.9525 - val_loss: 0.1548 - val_accuracy: 0.9415 - val_auc: 0.9849
Epoch 2/20
1123/1123 [==============================] - 26s 23ms/step - loss: 0.0796 - accuracy: 0.9729 - auc: 0.9951 - val_loss: 0.1550 - val_accuracy: 0.9457 - val_auc: 0.9862
Epoch 3/20
1123/1123 [==============================] - 26s 23ms/step - loss: 0.0327 - accuracy: 0.9901 - auc: 0.9986 - val_loss: 0.1744 - val_accuracy: 0.9508 - val_auc: 0.9841
Epoch 4/20
1123/1123 [==============================] - 25s 22ms/step - loss: 0.0168 - accuracy: 0.9948 - auc: 0.9994 - val_loss: 0.1844 - val_accuracy: 0.9497 - val_auc: 0.9822
Epoch 5/20
1123/1123 [==============================] - 26s 23ms/step - loss: 0.0102 - accuracy: 0.9967 - auc: 0.9997 - val_loss: 0.2891 - val_accuracy: 0.9416 - val_auc: 0.9675
Epoch 6/20
1123/1123 [==============================] - 26s 23ms/step - loss: 0.0074 - accuracy: 0.9979 - auc: 0.9997 - val_loss: 0.2298 - val_accuracy: 0.9516 - val_auc: 0.9756
Epoch 7/20
1123/1123 [==============================] - 25s 22ms/step - loss: 0.0057 - accuracy: 0.9981 - auc: 0.9998 - val_loss: 0.2585 - val_accuracy: 0.9506 - val_auc: 0.9722
Epoch 8/20
1123/1123 [==============================] - 25s 22ms/step - loss: 0.0061 - accuracy: 0.9982 - auc: 0.9998 - val_loss: 0.2368 - val_accuracy: 0.9537 - val_auc: 0.9755
Epoch 9/20
1123/1123 [==============================] - 25s 22ms/step - loss: 0.0061 - accuracy: 0.9981 - auc: 0.9998 - val_loss: 0.2821 - val_accuracy: 0.9491 - val_auc: 0.9705
Epoch 10/20
1123/1123 [==============================] - 26s 23ms/step - loss: 0.0031 - accuracy: 0.9992 - auc: 0.9999 - val_loss: 0.2865 - val_accuracy: 0.9518 - val_auc: 0.9704
Epoch 11/20
1123/1123 [==============================] - 25s 22ms/step - loss: 0.0044 - accuracy: 0.9986 - auc: 0.9999 - val_loss: 0.3036 - val_accuracy: 0.9483 - val_auc: 0.9681
Epoch 12/20
1123/1123 [==============================] - 25s 22ms/step - loss: 0.0049 - accuracy: 0.9986 - auc: 0.9998 - val_loss: 0.4864 - val_accuracy: 0.9156 - val_auc: 0.9427
Epoch 13/20
1123/1123 [==============================] - 25s 22ms/step - loss: 0.0037 - accuracy: 0.9989 - auc: 0.9999 - val_loss: 0.2758 - val_accuracy: 0.9531 - val_auc: 0.9708
Epoch 14/20
1123/1123 [==============================] - 26s 23ms/step - loss: 0.0020 - accuracy: 0.9996 - auc: 0.9999 - val_loss: 0.3219 - val_accuracy: 0.9496 - val_auc: 0.9671
Epoch 15/20
1123/1123 [==============================] - 26s 23ms/step - loss: 4.6594e-04 - accuracy: 0.9999 - auc: 1.0000 - val_loss: 0.3571 - val_accuracy: 0.9491 - val_auc: 0.9634
Epoch 16/20
1123/1123 [==============================] - 25s 22ms/step - loss: 3.2795e-04 - accuracy: 1.0000 - auc: 1.0000 - val_loss: 0.3868 - val_accuracy: 0.9480 - val_auc: 0.9610
Epoch 17/20
1123/1123 [==============================] - 25s 22ms/step - loss: 3.2790e-04 - accuracy: 1.0000 - auc: 1.0000 - val_loss: 0.3979 - val_accuracy: 0.9480 - val_auc: 0.9595
Epoch 18/20

```
1123/1123 [==============================] - 26s 23ms/step - loss: 3.2813e-04 - accuracy: 1.0000 - auc: 1.0000 - val_loss: 0.4101 - val_accuracy: 0.9469 - val_auc: 0.9588
Epoch 19/20
1123/1123 [==============================] - 25s 22ms/step - loss: 3.2916e-04 - accuracy: 1.0000 - auc: 1.0000 - val_loss: 0.4161 - val_accuracy: 0.9464 - val_auc: 0.9580
Epoch 20/20
1123/1123 [==============================] - 25s 22ms/step - loss: 3.2679e-04 - accuracy: 1.0000 - auc: 1.0000 - val_loss: 0.4322 - val_accuracy: 0.9463 - val_auc: 0.9562
```

Step 10 : Making Predictions

```
train_preds = model.predict(X_train_pad)
test_preds = model.predict(X_test_pad)
```

Output:

```
1123/1123 [==============================] - 7s 6ms/step
281/281 [==============================] - 2s 6ms/step
```

Step 11 : Examining Results

```
# Calculate log loss, ROC-AUC score, and confusion matrix for training set
train_loss = log_loss(y_train.map({'fake': 1, 'true': 0}), train_preds)
train_auc = roc_auc_score(y_train.map({'fake': 1, 'true': 0}), train_preds)
train_confusion = confusion_matrix(y_train.map({'fake': 1, 'true': 0}), train_preds > 0.5)

# Calculate log loss, ROC-AUC score, and confusion matrix for testing set
test_loss = log_loss(y_test.map({'fake': 1, 'true': 0}), test_preds)
```

```
test_auc = roc_auc_score(y_test.map({'fake': 1, 'true': 0}), test_preds)
test_confusion = confusion_matrix(y_test.map({'fake': 1, 'true': 0}),
test_preds > 0.5)

# print("Training Log Loss:", train_loss)
# print("Training ROC-AUC Score:", train_auc)
# print("Training Confusion Matrix:")
# print(train_confusion)
# print("Testing Log Loss:", test_loss)
# print("Testing ROC-AUC Score:", test_auc)
# print("Testing Confusion Matrix:")
# print(test_confusion)
```

```
from tabulate import tabulate
# ... Your previous code for metrics ...

# Tabulate metrics
table_data = [
    ["Training Log Loss", train_loss],
    ["Training ROC-AUC Score", train_auc],
#     ["Training Confusion Matrix", train_confusion],
    ["Testing Log Loss", test_loss],
    ["Testing ROC-AUC Score", test_auc],
#     ["Testing Confusion Matrix", test_confusion]
```

]

Print metrics as a table

print(tabulate(table_data, headers=["Metric", "Value"], tablefmt="pretty"))

Output:

```
+------------------------+-----------------------+
|         Metric         |         Value         |
+------------------------+-----------------------+
|   Training Log Loss    | 0.0003151029772055638 |
| Training ROC-AUC Score |  0.9999877151892584   |
|    Testing Log Loss    |  0.43219265655119493  |
| Testing ROC-AUC Score  |  0.9857079578396398   |
+------------------------+-----------------------+
```

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))

Plot Training Confusion Matrix

sns.heatmap(train_confusion, annot=True, fmt='d', cmap='Blues', ax=axes[0])

axes[0].set_title('Training Confusion Matrix')

Plot Testing Confusion Matrix

sns.heatmap(test_confusion, annot=True, fmt='d', cmap='Blues', ax=axes[1])

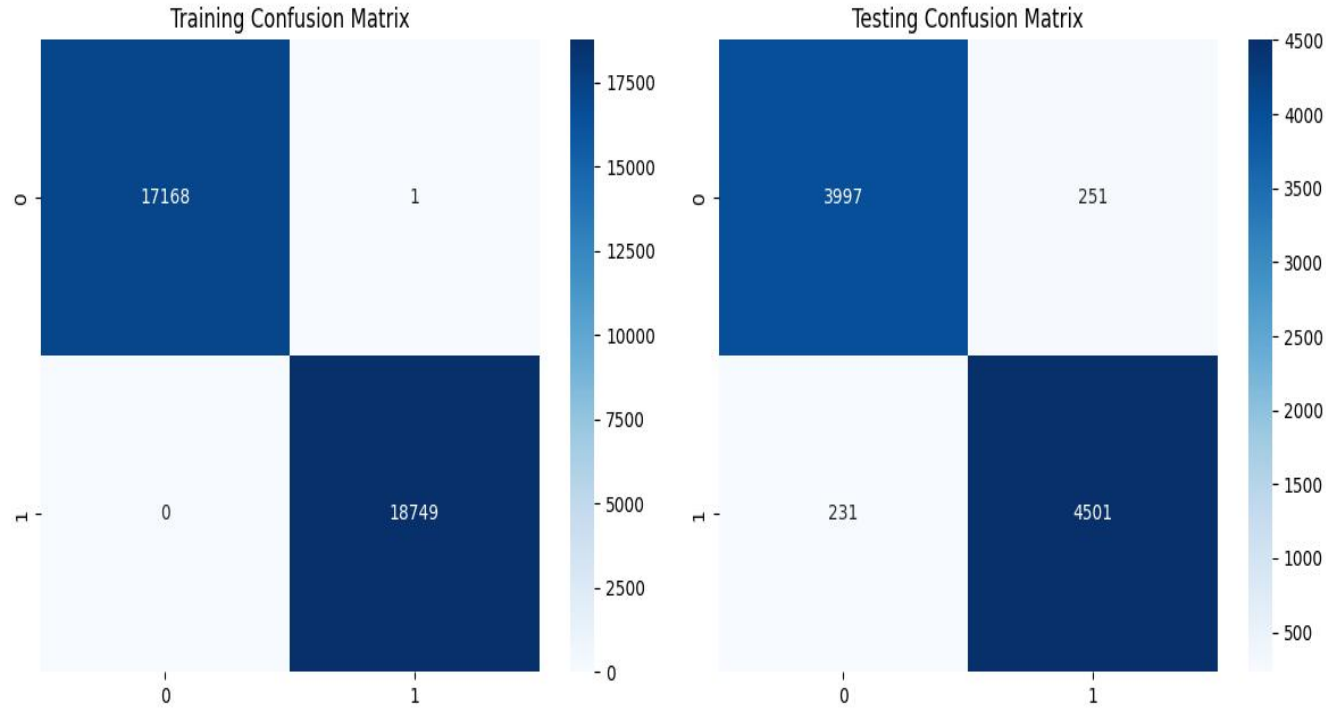
axes[1].set_title('Testing Confusion Matrix')

Adjust layout

plt.tight_layout()

plt.show()

Output:



Conclusion:

We have classified our news data using three classification models. We have analysed the performance of the models using accuracy and confusion matrix. But this is only a beginning point for the problem. There are advanced techniques like BERT, GloVe and ELMo which are popularly used in the field of NLP. If you are interested in NLP, you can work forward with these techniques.