news_classification_project

February 7, 2025

1 INTRODUCTION TO THE PROBLEM AND DATASET

1.1 PROBLEM STATEMENT

Over the years, inflation in India has averaged around 6%, yet many people still prefer traditional investment options like `Fixed Deposits (FDs) and Recurring Deposits (RDs), which often yield returns lower than inflation`. A common perception among Indians is that capital markets and investments are complex, requiring advanced financial knowledge. As a result, many `hesitate to explore stock markets and other investment opportunities, limiting their financial growth`.

To address this gap, a tech-driven platform was launched in 2020 with the goal of `simplifying finance and making investment decisions more accessible`. Using `artificial intelligence (AI) and machine learning (ML)`, the platform provides `smart news discovery, real-time stock insights, and a social community for discussions`. By delivering curated financial information in an easy-to-understand format, it empowers users—especially first-time investors—to make informed decisions with minimal effort.

1.2 OBJECTIVE OF THE PROJECT

The goal of this project is to classify news articles into categories like `politics, technology, sports, business, and entertainment` using `Natural Language Processing (NLP) and Machine Learning (ML)`. The project involves text preprocessing, feature extraction, and training multiple classification models.

At least three different models, including `Naïve Bayes, Decision Tree, and Random Forest`, will be implemented and compared to determine the best-performing approach.

1.3 IMPORT ALL THE REQUIRED LIBRARIES

[667]:
```python
# To ignore all warnings
import warnings

# for creating random numbers
import random

# for string operations
import string
```

```python
# for permutations and combinations
import itertools

# for proper display of dataframes and images
from IPython.display import display
from PIL import Image

# for saving the models
import pickle

# For reading & manipulating the data
import pandas as pd
import numpy as np

# For visualizing the data
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from pprint import pprint
from sklearn.manifold import TSNE
import matplotlib.patches as mpatches

# To use Regular Expressions
import re

# for parallel processing
import dask.dataframe as dd
import multiprocessing

# To display progress bars
from tqdm.notebook import tqdm

# for wordcloud
from wordcloud import WordCloud, STOPWORDS

# To use Natural Language Processing
import nltk
import spacy
from spacy.lang.en.stop_words import STOP_WORDS

# For tokenization
from nltk.tokenize import word_tokenize,sent_tokenize,TweetTokenizer
nltk.download('punkt')
nltk.download('punkt_tab')
nltk.download('wordnet')
nltk.download('omw-1.4')
nltk.download('averaged_perceptron_tagger')
```

```python
nltk.download('tagsets')
nltk.download('universal_tagset')
nltk.download('treebank')

# to expand contractions
import contractions

# To remove stopwords
from nltk.corpus import stopwords
nltk.download('stopwords')

# for stemming
from nltk.stem import PorterStemmer,LancasterStemmer,SnowballStemmer
# For lemmetization
from nltk import WordNetLemmatizer
nltk.download('wordnet')

# For BoW & TF-IDF
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

# For encoding the categorical variable
import category_encoders as ce
from sklearn.preprocessing import LabelEncoder,OneHotEncoder

# for word embeddings
from gensim.models import Word2Vec

#to detect language
from langdetect import detect,DetectorFactory

# To try out different ML models
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier,GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression

# To perform train-test split
from sklearn.model_selection import train_test_split,RandomizedSearchCV

# Performace Metrics for evaluating the model
from sklearn.metrics import accuracy_score, roc_auc_score, f1_score,␣
↪precision_score, recall_score
from sklearn.metrics import confusion_matrix,␣
↪classification_report,ConfusionMatrixDisplay
from sklearn.metrics.pairwise import cosine_similarity
```

```python
# Named Entity Recognition
from spacy import displacy

# for logging the metrics and artifacts
import mlflow
import mlflow.sklearn

warnings.simplefilter('ignore')
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package punkt_tab to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package omw-1.4 is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package tagsets to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package tagsets is already up-to-date!
[nltk_data] Downloading package universal_tagset to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package universal_tagset is already up-to-date!
[nltk_data] Downloading package treebank to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package treebank is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\saina\AppData\Roaming\nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

1.4 IMPORT DATASET

[516]:
```python
data = pd.read_csv(r"C:
↪\Users\saina\Desktop\DS_ML_AI\Scaler\Module_21_NLP\Case_studies\other\news-data.
↪csv")
```

[517]:
```python
data.sample(10,random_state=42)
```

[517]:
```
          Category                                            Article
414       Politics  brown and blair face new rift claims for the u…
420       Business  small firms  hit by rising costs  rising fuel …
1644 Entertainment  spirit awards hail sideways the comedy sideway…
416     Technology  microsoft releases patches microsoft has warne…
1232        Sports  arsenal through on penalties arsenal win 4-2 o…
1544      Business  jobs go at oracle after takeover oracle has an…
1748      Business  id theft surge hits us consumers almost a quar…
1264        Sports  poll explains free-kick decision referee graha…
629         Sports  parmar ruled out of davis cup tie a knee injur…
1043    Technology  video phones act as dating tools technologies …
```

1.5 DESCRIPTION REGARDING EACH COLUMN OF THE DATASET

[518]:
```python
data["Category"].unique()
```

[518]:
```
array(['Technology', 'Business', 'Sports', 'Entertainment', 'Politics'],
      dtype=object)
```

Column Name	Description
Category	Category of Article ['Technology', 'Business', 'Sports', 'Entertainment', 'Politics'] (Target Variable of the dataset)
Article	Text Extracted from News Article

2 EDA, VISUALISATION AND TRAIN TEST SPLIT

2.1 SHAPE OF THE DATA

[519]:
```python
print(f"Number of rows in the dataset = {data.shape[0]}")
print(f"Number of columns in the dataset = {data.shape[1]}")
```

```
Number of rows in the dataset = 2225
Number of columns in the dataset = 2
```

2.2 DATASET INFO

[520]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2225 entries, 0 to 2224
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Category  2225 non-null   object
 1   Article   2225 non-null   object
dtypes: object(2)
memory usage: 34.9+ KB
```

2.3 NULL VALUE DETECTION

[521]:
```
# Null value count
data.isnull().sum()
```

[521]:
```
Category    0
Article     0
dtype: int64
```

Observation > No Null Values in the dataset

2.4 DESCRIPTIVE STATISTICS

[522]:
```
data.describe()
```

[522]:

	Category	Article
count	2225	2225
unique	5	2126
top	Sports	kennedy questions trust of blair lib dem leade…
freq	511	2

Observation > There is difference between count and unique value of Article. So Duplicated Articles are present in the "Article" Column.

Frequency of any article should be 1.

2.5 DUPLICATED ARTICLES DETECTION AND REMOVAL

[523]:
```
data.duplicated().sum()
```

[523]: 99

[524]:
```
2225-2126
```

[524]: 99

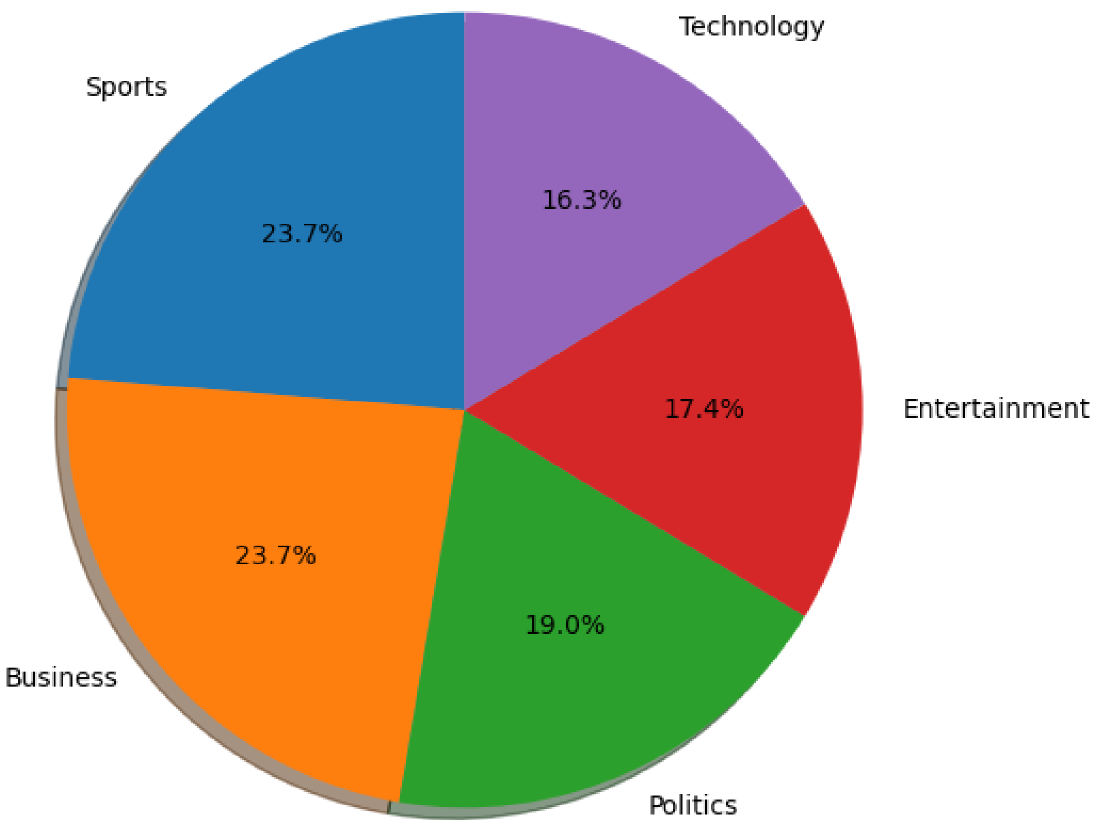
[525]:
```
# Removing the duplicates
data.drop_duplicates(inplace=True)
```

2.6 VALUE COUNTS OF CATEGORY AND PIE CHART VISUALISATION

[526]:
```
def pie_chart(dataframe):
    label_counts = dataframe.Category.value_counts()

    print('Labels in the dataset: ', label_counts.index.tolist())
    print(label_counts)

    labels = label_counts.index  # Corrected: Ensure labels match their counts
    sizes = label_counts.values  # Get counts directly
```

```
    plt.figure(figsize=(6, 6))
    plt.pie(sizes, labels=labels, autopct='%1.1f%%', shadow=True, startangle=90)
    plt.axis('equal')  # Keep the pie chart circular
    plt.show()

pie_chart(data)
```

```
Labels in the dataset:  ['Sports', 'Business', 'Politics', 'Entertainment',
'Technology']
Category
Sports           504
Business         503
Politics         403
Entertainment    369
Technology       347
Name: count, dtype: int64
```



2.7 TRAIN TEST SPLIT STRATIFY BY CATEGORY

[527]:
```
# Assuming 'data' is already loaded with the 'Category' column
# Split the dataset into features (X) and labels (y)
X = data['Article'].astype(str)
y = data['Category']

# Perform 80/20 split with stratification based on the 'Category' column
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42, stratify=y)

# Print the size of the training and testing datasets
print(f"Size of training dataset: {len(X_train)}")
print(f"Size of testing dataset: {len(X_test)}")
```

```
Size of training dataset: 1700
Size of testing dataset: 426
```

[528]:
```
X_train = pd.DataFrame(X_train,columns=["Article"])
X_test = pd.DataFrame(X_test,columns=["Article"])
y_train = pd.DataFrame(y_train,columns=["Category"])
y_test = pd.DataFrame(y_test,columns=["Category"])
```

3 TEST PROCESSING

[529]:
```
categories = data["Category"].unique()
```

3.1 BEFORE PREPROCESSING

[530]:
```
# Sample articles from each category along with index
for category in categories:
    sample = X_train[y_train == category].sample(1, random_state=42)  # Select␣
↪random article
    index = sample.index[0]  # Get index
    article = sample.values[0]  # Get article content
    print(f'\n{category} article (Index {index}): {article}')
```

```
Technology article (Index 881): [nan]

Business article (Index 881): [nan]

Sports article (Index 881): [nan]

Entertainment article (Index 881): [nan]

Politics article (Index 881): [nan]
```

[531]:
```
list_of_X_train_sample_articles_index = [462,39,936,1048,104]
```

3.2 TEST PREPROCESSING FUNCTIONS

[532]:
```
sample = "Hello123!, I d like to test the articles."
```

3.2.1 Function for Expanding Contractions

[533]:
```
# Function to expand contractions
def expand_contractions(text):
    # Extract contractions and convert keys to lowercase
    contraction_map = {c.lower(): contractions.fix(c).lower() for c in␣
 ↪contractions.contractions_dict.keys()}

    # Create a modified version with spaces instead of apostrophes
    contraction_map_with_spaces = {k.replace("'", " "): v for k, v in␣
 ↪contraction_map.items()}

    # Create regex pattern to match contractions with spaces
    pattern = re.compile(r'\b(' + '|'.join(re.escape(k) for k in␣
 ↪contraction_map_with_spaces.keys()) + r')\b')

    # Expand contractions
    return pattern.sub(lambda x: contraction_map_with_spaces[x.group()], text)
```

[534]:
```
sample = expand_contractions(sample.lower())
print(sample)
```

```
hello123!, i would like to test the articles.
```

3.2.2 Function for removing all the non-letters like numbers, punctuations, symbols etc.,

[535]:
```
# Function to remove non-letters
def remove_non_letters(text):
    return re.sub(r'[^a-zA-Z\s]', '', text)
```

[536]:
```
sample = remove_non_letters(sample)
print(sample)
```

```
hello i would like to test the articles
```

3.2.3 NLTK Word tokenization

[537]:
```
words = word_tokenize(sample)
print(words)
```

```
['hello', 'i', 'would', 'like', 'to', 'test', 'the', 'articles']
```

3.2.4 Remove the Stopwords using nltk corpus stopwords

[538]:
```
english_stopwords = set(stopwords.words('english'))
words = [word for word in words if word not in english_stopwords]
print(words)
```

```
['hello', 'would', 'like', 'test', 'articles']
```

3.2.5 Wordnet Lemmatization

[539]:
```
lemmatizer = WordNetLemmatizer()
words = [lemmatizer.lemmatize(word) for word in words]
print(words)
```

```
['hello', 'would', 'like', 'test', 'article']
```

3.2.6 Join the words again

[540]:
```
cleaned_text = ' '.join(words)
print(cleaned_text)
```

```
hello would like test article
```

3.2.7 Total text preprocessing function

[541]:
```
# Function to preprocess text
def preprocess_text(text):
    # Step 1: Convert to lowercase
    text = text.lower()

    # Step 2: Expand contractions
    text = expand_contractions(text)

    # Step 3: Remove non-letter characters (keep spaces)
    text = remove_non_letters(text)

    # Step 4: Tokenization
    words = word_tokenize(text)

    # Step 5: Remove stop words
    english_stop_words = set(stopwords.words('english'))
    words = [word for word in words if (word not in english_stop_words) and␣
 ↪(word not in string.punctuation) ]

    # Step 6: Lemmatization
    lemmatizer = WordNetLemmatizer()
    words = [lemmatizer.lemmatize(word) for word in words]

    # Step 7: Join the words back into a single string
```

```
    cleaned_text = ' '.join(words)

    return cleaned_text
```

[542]:
```
sample = "Hello123!, I d like to test the articles."
sample = preprocess_text(sample)
print(sample)
```

```
hello would like test article
```

[543]:
```
X_train_preprocessed = X_train['Article'].apply(preprocess_text)
```

[544]:
```
X_test_preprocessed = X_test["Article"].apply(preprocess_text)
```

[545]:
```
X_train_preprocessed = pd.DataFrame(X_train_preprocessed,columns=["Article"])
X_test_preprocessed = pd.DataFrame(X_test_preprocessed,columns=["Article"])
```

3.2.8 Saving all the files

[546]:
```
# Define a function to save all the variables
def save_data(X_train, y_train, X_test, y_test, X_train_preprocessed,␣
 ↪X_test_preprocessed, filename_prefix):
    # Save the data to separate pickle files
    with open(f'{filename_prefix}_X_train.pkl', 'wb') as f:
        pickle.dump(X_train, f)

    with open(f'{filename_prefix}_y_train.pkl', 'wb') as f:
        pickle.dump(y_train, f)

    with open(f'{filename_prefix}_X_test.pkl', 'wb') as f:
        pickle.dump(X_test, f)

    with open(f'{filename_prefix}_y_test.pkl', 'wb') as f:
        pickle.dump(y_test, f)

    with open(f'{filename_prefix}_X_train_preprocessed.pkl', 'wb') as f:
        pickle.dump(X_train_preprocessed, f)

    with open(f'{filename_prefix}_X_test_preprocessed.pkl', 'wb') as f:
        pickle.dump(X_test_preprocessed, f)

    print("Data saved successfully.")

# Save all the data
save_data(X_train, y_train, X_test, y_test, X_train_preprocessed,␣
 ↪X_test_preprocessed, 'news_data')
```

```
Data saved successfully.
```

```
[547]: # def load_data(filename_prefix):
#     with open(f'{filename_prefix}_X_train.pkl', 'rb') as f:
#         X_train = pickle.load(f)

#     with open(f'{filename_prefix}_y_train.pkl', 'rb') as f:
#         y_train = pickle.load(f)

#     with open(f'{filename_prefix}_X_test.pkl', 'rb') as f:
#         X_test = pickle.load(f)

#     with open(f'{filename_prefix}_y_test.pkl', 'rb') as f:
#         y_test = pickle.load(f)

#     with open(f'{filename_prefix}_X_train_preprocessed.pkl', 'rb') as f:
#         X_train_preprocessed = pickle.load(f)

#     with open(f'{filename_prefix}_X_test_preprocessed.pkl', 'rb') as f:
#         X_test_preprocessed = pickle.load(f)

#     return X_train, y_train, X_test, y_test, X_train_preprocessed,␣
↪X_test_preprocessed

# # Load the data
# X_train, y_train, X_test, y_test, X_train_preprocessed, X_test_preprocessed =␣
↪load_data('news_data')

# print("Data loaded successfully.")
```

3.3 AFTER PREPROCESSING

```
[548]: # Print cleaned articles in the same order along with category
for index in list_of_X_train_sample_articles_index:
    category = y_train.loc[index]  # Get category name
    article = X_train["Article"].loc[index]  # Get original article
    preprocessed_article = X_train_preprocessed["Article"].loc[index]  # Get␣
↪preprocessed article
    print(f'\n{category}:\n Original article:\t{article}\n Preprocessed article:
↪\t{preprocessed_article}')
```

```
Category    Technology
Name: 462, dtype: object:
 Original article:     musical future for phones analyst bill thompson has seen
the future and it is in his son s hands.  i bought my son max a 3g phone  partly
because they are so cheap and he needed a phone  and partly because i am
supposed to know about the latest technology and thought i should see how they
work in real life. after using it for a while i am not at all tempted to get rid
of my sonyericsson p800 smart phone. that has a relatively large screen  even if
```

it does only have slower gprs access to the network. i can read my e-mail surf the web using a proper browser and write stuff using the stylus on its touch screen. last week someone e-mailed me a document that had been compressed into a zip file and i was pleasantly surprised to discover that my phone even knew how to decompress it for me. by contrast the confusing menus complicated keyboard and truly irritating user interface of max s 3g phone simply get in the way and i did not see much value in the paid-for services especially the limited web access. the videos of entertainment news horoscopes and the latest celebrity gossip did not appeal and i did not see how the small screen could be useful for any sort of image never mind micro-tv. but then max started playing and i realised i was missing the point entirely. it is certainly not a great overall experience but that is largely due to the poor menu system and the phone layout: the video content itself is compelling. the quality was at least as good as the video streaming from the bbc website and the image is about the same size. max was completely captivated and i was intrigued to discover that i had nearly missed the next stage of the network revolution. it is easy to be dismissive of small screens and indeed anyone of my generation with failing eyesight and the view that there s never anything worth watching on tv   is hardly going to embrace these phones. but just as the world wide web was the killer application that drove internet adoption music videos are going to drive 3g adoption. with vodafone now pushing its own 3g service and 3 already established in the uk video on the phone is clearly going to become a must-have for kids sitting on the school bus adults waiting outside clubs and anyone who has time to kill and a group of friends to impress. this will please the network operators who are looking for some revenue from their expensively acquired 3g licences. but it goes deeper than that: playing music videos on a phone marks the beginning of a move away from the download and play model we have all accepted for our ipods and mp3 players. after all why should i want to carry 60gb of music and pictures around with me in my pocket when i can simply listen to anything i want whenever i want streamed to my phone oh - and of course you can always use the phone to make voice calls and send texts something which ensures that it is always in someone s pocket or handbag available for other uses too. i have never really approved of using the internet protocol (ip) to do either audio or video streaming and i think that technically it is a disaster to make phone calls over the net using voice over ip . but i have to acknowledge that the net at least here in the developed western countries is fast and reliable enough to do both. i stream radio to my computer while i work and enjoy hearing the bizarre stations from around the world that i can find online but nowhere else. i am even playing with internet telephony despite my reservations and i appear on go digital on the world service streamed over the web each week. but 3g networks have been designed to do this sort of streaming both for voice and video which gives them an edge over net-based ip services. the 3g services aren t quite there yet and there is a lot to be sorted out when it comes to web access and data charges. vodafone will let you access its services on vodafone live! as part of your subscription cost but it makes you pay by the megabyte to download from other sites - this one for example. this will not matter to business users but will distort the consumer market and keep people within the phone company s collection of partner sites something that should perhaps be worrying telecoms regulator ofcom. but we should not see these new phones simply as cut-down network terminals. if i want fast access to my e-mail i can get a 3g card for my laptop or hook up to a wireless network. the phone is a lot more and it is as a combination of mini-tv personal communications device and music/video player that it really works. there is certainly room in the technology ecosystem for many different sorts of devices accessing a wide range of services over different networks. 3g phones and ipods can co-exist at least for a while but if i had to bet on the long term i would go for content on demand over carrying gigabytes in my pocket. or perhaps some enterprising manufacturer will offer me both. an mp3g player anyone   bill thompson is a regular commentator on the bbc world service programme go digital.

Preprocessed article: musical future phone analyst bill thompson seen future son hand bought son max g phone partly cheap needed phone partly supposed know latest technology thought see work real life using tempted get rid sonyericsson p smart phone relatively large screen even slower gprs access network read email surf web using proper browser write stuff using stylus touch screen last week someone emailed document compressed zip file pleasantly surprised discover phone even knew decompress contrast confusing menu complicated keyboard truly irritating user interface max g phone simply get way see much value paidfor service especially limited web access video entertainment news horoscope latest celebrity gossip appeal see small screen could useful sort image never mind microtv max started playing realised missing point entirely certainly great overall experience largely due poor menu system phone layout video content compelling quality least good video streaming bbc website image size max completely captivated intrigued discover nearly missed next stage network revolution easy dismissive small screen indeed anyone generation failing eyesight view never anything worth watching tv hardly going embrace phone world wide web killer application drove internet adoption music video going drive g adoption vodafone pushing g service already established uk video phone clearly going become musthave kid sitting school bus adult waiting outside club anyone time kill group friend impress please network operator looking revenue expensively acquired g licence go deeper playing music video phone mark beginning move away download play model accepted ipod mp player want carry gb music picture around pocket simply listen anything want whenever want streamed phone oh course always use phone make voice call send text something ensures always someone pocket handbag available us never really approved using internet protocol ip either audio video streaming think technically disaster make phone call net using voice ip acknowledge net least developed western country fast reliable enough stream radio computer work enjoy hearing bizarre station around world find online nowhere else even playing internet telephony despite reservation appear go digital world service streamed web week g network designed sort streaming voice video give edge netbased ip service g service quite yet lot sorted come web access data charge vodafone let access service vodafone live part subscription cost make pay megabyte download site one example matter business user distort consumer market keep people within phone company collection partner site something perhaps worrying telecom regulator ofcom see new phone simply cutdown network terminal want fast access email get g card laptop hook wireless network phone lot combination minitv personal communication device musicvideo player really work certainly room technology ecosystem many different sort device accessing wide range service different network g phone ipod coexist least bet long term would go content demand carrying gigabyte pocket perhaps enterprising manufacturer offer mpg player anyone bill thompson regular commentator bbc world service programme go digital

Category   Business
Name: 39, dtype: object:
 Original article: german growth goes into reverse germany s economy shrank 0.2% in the last three months of 2004 upsetting hopes of a sustained recovery. the figures confounded hopes of a 0.2% expansion in the fourth quarter in europe s biggest economy. the federal statistics office said growth for the whole of 2004 was 1.6% after a year of contraction in 2003 down from an earlier estimate of 1.7%. it said growth in the third quarter had been zero putting the economy at a standstill from july onward. germany has been reliant on exports to get its economy back on track as unemployment of more than five million and impending cuts to welfare mean german consumers have kept their money to themselves. major companies including volkswagen daimlerchrysler and siemens have spent much of 2004 in tough talks with unions about trimming jobs and costs. according to the statistics office destatis rising exports were outweighed in the fourth quarter by the continuing weakness of domestic demand. but the relentless rise in the value of the euro last year has also hit the competitiveness of german products overseas. the effect has been to depress prospects for the 12-nation eurozone as a whole as well as germany. eurozone interest rates are at 2% but senior officials at the rate-setting european central bank are beginning to talk about the threat of inflation prompting fears that interest rates may rise. the ecb s mandate is to fight rising prices by boosting interest rates - and that could further threaten germany s hopes of recovery.
 Preprocessed article: german growth go reverse germany economy shrank last three month upsetting hope sustained recovery figure confounded hope expansion fourth quarter europe biggest economy federal statistic office said growth whole year contraction earlier estimate said growth third quarter zero putting economy standstill july onward germany reliant export get economy back track unemployment five million impending cut welfare mean german consumer kept money major company including volkswagen daimlerchrysler siemens spent much tough talk union trimming job cost according statistic office destatis rising export outweighed fourth quarter continuing weakness domestic demand relentless rise value euro last year also hit competitiveness german product overseas effect depress prospect nation eurozone whole well germany eurozone interest rate senior official ratesetting european central bank beginning talk threat inflation prompting fear interest rate may rise ecb mandate fight rising price boosting interest rate could threaten germany hope recovery

Category   Sports
Name: 936, dtype: object:
 Original article: charvis set to lose fitness bid flanker colin charvis is

unlikely to play any part in wales final two games of the six nations. charvis has missed all three of wales victories with an ankle injury and his recovery has been slower than expected. he will not figure in the scotland game and is now thought unlikely to be ready for the final game   said wales physio mark davies. sonny parker is continuing to struggle with a neck injury but hal luscombe should be fit for the murrayfield trip. centre parker has only a slim chance of being involved against the scots on 13 march so luscombe s return to fitness after missing the france match with hamstring trouble is a timely boost. said wales assistant coach scott johnson: we re positive about hal and hope he ll be raring to go. he comes back into the mix again adds to the depth and gives us other options.   replacement hooker robin mcbryde remains a doubt after picking up knee ligament damage in paris last saturday. we re getting that reviewed and we should know more by the end of the week how robin s looking added johnson. we re hopeful but it s too early to say at this stage. steve jones from the dragons is likely to be drafted in if mcbryde fails to recover.
Preprocessed article: charvis set lose fitness bid flanker colin charvis unlikely play part wale final two game six nation charvis missed three wale victory ankle injury recovery slower expected figure scotland game thought unlikely ready final game said wale physio mark davy sonny parker continuing struggle neck injury hal luscombe fit murrayfield trip centre parker slim chance involved scot march luscombe return fitness missing france match hamstring trouble timely boost said wale assistant coach scott johnson positive hal hope raring go come back mix add depth give u option replacement hooker robin mcbryde remains doubt picking knee ligament damage paris last saturday getting reviewed know end week robin looking added johnson hopeful early say stage steve jones dragon likely drafted mcbryde fails recover

Category   Entertainment
Name: 1048, dtype: object:
Original article: de niro film leads us box office film star robert de niro has returned to the top of the north american box office with his film hide and seek. the thriller shot straight to the number one spot after taking $22m (£11.7m) at the box office. de niro recently spent three weeks at the top with comedy meet the fockers which was at number five this week. oscar hopefuls the aviator million dollar baby and sideways all cashed in on their multiple nominations with stronger ticket sales. in hide and seek de niro plays a widower whose daughter has a creepy imaginary friend. despite lukewarm reviews from critics the film took more than the expected $18m (£9.5m). the element of a real actor in a psychological thriller certainly elevated it   said bruce snyder president of domestic distribution at 20th century fox. clint eastwood s million dollar baby led the oscar hopefuls with $11.8m (£6.3m) coming in at number three during its first weekend of wide release. the aviator a film biography of howard hughes that leads the oscar field with 11 nominations was at number six for the weekend with $7.5m (£4m). oscar best-picture nominee sideways entered the top ten for the first time in its 15th week of release. it came in seventh $6.3 (£3.35m). last week s top film ice cube s road-trip comedy are we there yet   slipped to second place with $17m (£9m) while coach carter fell two places to number four taking $8m (£4.25m) in its third week. rounding

out the top ten were in good company - starring dennis quaid and scarlett johansson - racing stripes and assault on precinct 13.

Preprocessed article: de niro film lead u box office film star robert de niro returned top north american box office film hide seek thriller shot straight number one spot taking box office de niro recently spent three week top comedy meet fockers number five week oscar hopeful aviator million dollar baby sideways cashed multiple nomination stronger ticket sale hide seek de niro play widower whose daughter creepy imaginary friend despite lukewarm review critic film took expected element real actor psychological thriller certainly elevated said bruce snyder president domestic distribution th century fox clint eastwood million dollar baby led oscar hopeful coming number three first weekend wide release aviator film biography howard hughes lead oscar field nomination number six weekend oscar bestpicture nominee sideways entered top ten first time th week release came seventh last week top film ice cube roadtrip comedy yet slipped second place coach carter fell two place number four taking third week rounding top ten good company starring dennis quaid scarlett johansson racing stripe assault precinct

Category   Politics
Name: 104, dtype: object:

Original article: howard pitches for uk ethnic vote michael howard is to make a pitch for britain s ethnic vote urging people who feel taken for granted by tony blair to vote conservative. he will say conservatives share the same values as the uk s minorities. and that he wants to build a better britain where everyone whatever the colour of their skin or religion can make the most of their talents . but the tory leader will argue against positive discrimination saying it is outdated and unjust .   it sets family against family and it leads ethnic communities to doubt their own abilities   he will argue. mr howard - himself the son of immigrants - will acknowledge that racial discrimination still exists in the uk. people from ethnic communities for example still earn less than their white counterparts   he will say before arguing the answer to helping everyone to get on was free enterprise free trade free speech . the tory leader will also call for religious tolerance arguing that hindus and sikhs as well as muslims got caught in the downdraft of islamaphobia which was one of the terrible side effects of 9/11 . mr howard will make his speech during a visit to support tory parliamentary hopefuls robert light and sayeeda warsi - the first british muslim woman selected to run for mp as a conservative candidate. he will attack labour s record in government over issues such as tax and he will set out tory plans for an immigration quota to be set by mps. mr howard will also attack the lib dems for wanting to abolish faith schools introduce compulsory sex education from the age of seven and give contraceptives out in schools from the age of 11 . so i say to all those people from ethnic minorities who feel mr blair and the liberal democrats take their votes for granted - come join us   he will say. lib dem president simon hughes branded mr howard arrogant and wrong for claiming the tories were the natural party for britain s ethnic minorities. given the tories considerably reduced support in urban areas where many black and asian britons live during their time in power the evidence simply does not support

```
his claims that the conservatives are the party for these communities   he said.
 Preprocessed article:  howard pitch uk ethnic vote michael howard make pitch
britain ethnic vote urging people feel taken granted tony blair vote
conservative say conservative share value uk minority want build better britain
everyone whatever colour skin religion make talent tory leader argue positive
discrimination saying outdated unjust set family family lead ethnic community
doubt ability argue mr howard son immigrant acknowledge racial discrimination
still exists uk people ethnic community example still earn less white
counterpart say arguing answer helping everyone get free enterprise free trade
free speech tory leader also call religious tolerance arguing hindu sikh well
muslim got caught downdraft islamaphobia one terrible side effect mr howard make
speech visit support tory parliamentary hopeful robert light sayeeda warsi first
british muslim woman selected run mp conservative candidate attack labour record
government issue tax set tory plan immigration quota set mp mr howard also
attack lib dems wanting abolish faith school introduce compulsory sex education
age seven give contraceptive school age say people ethnic minority feel mr blair
liberal democrat take vote granted come join u say lib dem president simon
hughes branded mr howard arrogant wrong claiming tory natural party britain
ethnic minority given tory considerably reduced support urban area many black
asian briton live time power evidence simply support claim conservative party
community said
```

4 ENCODING

4.0.1 Encoding the "Category" Column

[549]:
```
# Initialize and fit LabelEncoder
label_encoder = LabelEncoder()
y_train['Category_Encoded'] = label_encoder.fit_transform(y_train['Category'])
y_test["Category_Encoded"] = label_encoder.transform(y_test["Category"])
```

[550]:
```
y_train.sample(5,random_state=100)
```

[550]:

	Category	Category_Encoded
1398	Technology	4
1126	Sports	3
1795	Entertainment	1
1717	Politics	2
501	Business	0

[551]:
```
# Save the label encoder for deployment
with open("label_encoder.pkl", "wb") as file:
    pickle.dump(label_encoder, file)
```

[552]:
```
# # load the label encoder
# with open("label_encoder.pkl", "rb") as file:
#     label_encoder = pickle.load(file)
```

[553]:
```
y_train_preprocessed = y_train["Category_Encoded"]
y_test_preprocessed = y_test["Category_Encoded"]
```

5 DOCUMENT CLASSIFICATION USING WORD & CATEGORY & FREQUENCY DICTIONARY

5.1 BUILD FREQUENCY DICTIONRY USING PAIRS OF WORDS AND CATEGORY

[554]:
```
def build_freqs(articles, ys):
    yslist = np.squeeze(ys).tolist()
    freqs = {}
    for y, articles in zip(yslist, articles):
        for word in articles.split():
            pair = (word, y)
            if pair in freqs:
                freqs[pair] += 1
            else:
                freqs[pair] = 1

    return freqs
```

[555]:
```
# create frequency dictionary
freqs = build_freqs(X_train_preprocessed["Article"], y_train_preprocessed)

# check data type
print(f'type(freqs) = {type(freqs)}')

# check length of the dictionary
print(f'len(freqs) = {len(freqs)}')
```

```
type(freqs) = <class 'dict'>
len(freqs) = 46436
```

[556]:
```
random.seed(42)
random.sample(list(freqs.items()),20)
```

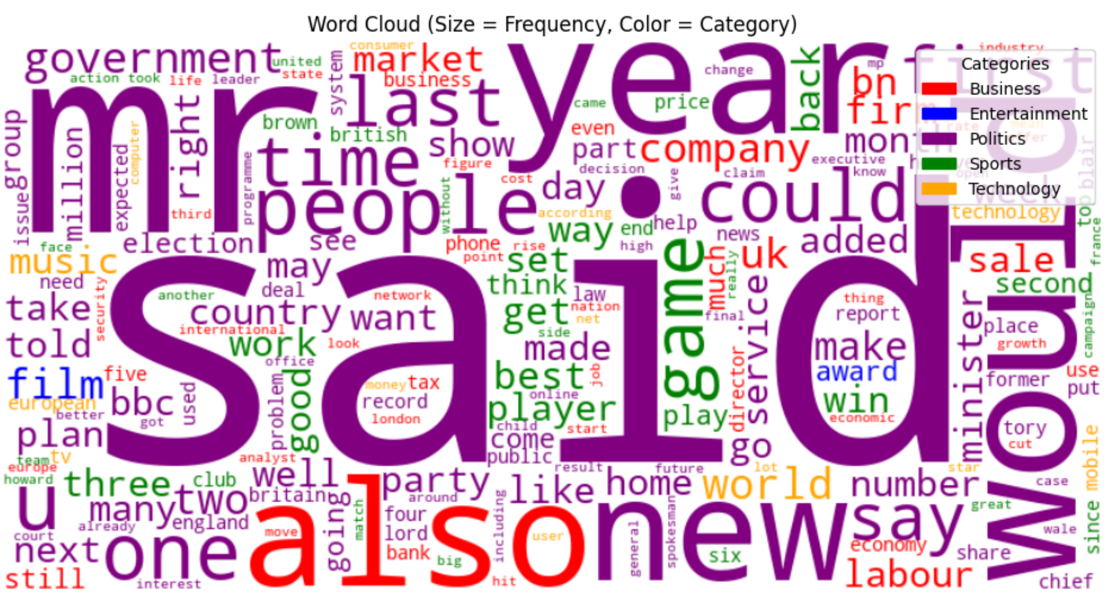
[556]:
```
[(('bellow', 1), 2),
 (('collaboration', 0), 2),
 (('frontrow', 3), 1),
 (('extended', 1), 4),
 (('runnersup', 1), 3),
 (('wider', 4), 7),
 (('sadly', 2), 7),
 (('niggly', 3), 1),
 (('diligence', 2), 1),
 (('rolf', 1), 1),
```

```
(('professor', 2), 12),
(('bertie', 0), 1),
(('serbia', 3), 4),
(('step', 0), 24),
(('news', 0), 117),
(('worm', 4), 30),
(('demanded', 3), 2),
(('alcohol', 1), 5),
(('conquer', 1), 1),
(('appelas', 1), 1)]
```

5.2 WORDCLOUD VISUALISATION OF FREQS DICTIONARY

[557]:
```
# Decode category labels using label encoder
category_labels = label_encoder.inverse_transform(np.
 ↪unique(y_train_preprocessed))  # Get original category names

# Define distinct colors for each category
category_colors = {
    category_labels[0]: 'red',
    category_labels[1]: 'blue',
    category_labels[2]: 'purple',
    category_labels[3]: 'green',
    category_labels[4]: 'orange'
}

# Convert frequency dictionary into a usable format
word_freq = {}  # {word: frequency}
word_category = {}  # {word: category (decoded)}

for (word, category), count in freqs.items():
    decoded_category = label_encoder.inverse_transform([category])[0]  #␣
 ↪Convert label back to category name

    if word in word_freq:
        word_freq[word] += count  # Sum frequencies if word appears in multiple␣
 ↪categories
    else:
        word_freq[word] = count
        word_category[word] = decoded_category  # Assign the decoded category␣
 ↪to the word

# Custom function to color words based on category
def color_func(word, font_size, position, orientation, random_state=None,␣
 ↪**kwargs):
    return category_colors.get(word_category.get(word, 'black'), 'black')  #␣
 ↪Default to black if not found
```

```
# Generate word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white').
 ↪generate_from_frequencies(word_freq)

# Plot the word cloud with coloring
plt.figure(figsize=(12, 6))
plt.imshow(wordcloud.recolor(color_func=color_func), interpolation="bilinear")
plt.axis("off")
plt.title("Word Cloud (Size = Frequency, Color = Category)")

# Create legend patches for category colors
legend_patches = [mpatches.Patch(color=color, label=category) for category,␣
 ↪color in category_colors.items()]

# Add legend
plt.legend(handles=legend_patches, title="Categories", loc="upper right",␣
 ↪fontsize=10, frameon=True)

plt.show()
```



5.3 EXTRACTING FEATURES FROM FREQUENCY DICTIONARY

[558]:
```
y_train["Category"].unique()
```

[558]:
```
array(['Politics', 'Business', 'Sports', 'Technology', 'Entertainment'],
      dtype=object)
```

[559]:
```python
def extract_features(article, freqs, categories = [0,1,2,3,4]):
    # Initialize a feature vector of size (1, len(categories) + 1) [bias term +␣
↪category counts]
    x = np.zeros((1, len(categories) + 1))

    # Bias term is set to 1
    x[0, 0] = 1

    # Loop through each word in the processed article
    for word in article.split():
        for i, category in enumerate(categories):
            # Increment word count for the respective category
            x[0, i + 1] += freqs.get((word, category), 0)

    assert x.shape == (1, len(categories) + 1)
    return x
```

[560]:
```python
sample = X_train_preprocessed["Article"].iloc[2]
print(f'Sample article:\n{sample}\n')
print(extract_features(sample, freqs))
```

```
Sample article:
pension hitch longliving men male life expectancy much higher originally
estimated leading pension researcher said pension policy institute ppi said life
expectancy unskilled professional men understated life expectancy birth year
manual worker year professional gap eight year measured age instead ppi said
manual worker live year professional worker year gap five year ppi estimate
higher excludes people died reach year age also take account ongoing improvement
life expectancy government ruled raising state pension age say would penalise
lowerskilled worker generally lower life expectancy chris curry ppi research
director said calculation suggested could pressure state pension spending
originally envisaged even people social class v unskilled manual worker widely
likely lowest life expectancy still expect live year state pension age said
researcher updated life expectancy projection woman average live longer men

[[1.0000e+00 1.7340e+04 9.9600e+03 1.8338e+04 9.1710e+03 1.3470e+04]]
```

[561]:
```python
categories = [0,1,2,3,4]

# Initialize feature matrix 'X' with shape (num_samples, num_categories + 1)
X_train_preprocessed_features = np.zeros((len(X_train_preprocessed),␣
↪len(categories) + 1))

# Extract features for each article in X_train_preprocessed
for i in range(len(X_train_preprocessed)):
    X_train_preprocessed_features[i, :] =␣
↪extract_features(X_train_preprocessed["Article"].iloc[i], freqs, categories)
```

```
# Print output
print("Feature Matrix Shape:", X_train_preprocessed_features.shape)
```

```
Feature Matrix Shape: (1700, 6)
```

[562]:
```
X_train_preprocessed_features[0]
```

[562]:
```
array([1.0000e+00, 2.8130e+04, 1.5760e+04, 4.6777e+04, 1.7785e+04,
       2.7203e+04])
```

[563]:
```
categories = [0,1,2,3,4]

# Initialize feature matrix 'X' with shape (num_samples, num_categories + 1)
X_test_preprocessed_features = np.zeros((len(X_test_preprocessed),␣
 ↪len(categories) + 1))

# Extract features for each article in X_test_preprocessed
for i in range(len(X_test_preprocessed)):
    X_test_preprocessed_features[i, :] =␣
 ↪extract_features(X_test_preprocessed["Article"].iloc[i], freqs, categories)

# Print output
print("Feature Matrix Shape:", X_test_preprocessed_features.shape)
```

```
Feature Matrix Shape: (426, 6)
```

[564]:
```
X_test_preprocessed_features[0]
```

[564]:
```
array([1.0000e+00, 2.1923e+04, 1.1199e+04, 2.7130e+04, 1.1431e+04,
       1.9079e+04])
```

5.4 SIMPLE LOGISTIC REGRESSION

[576]:
```
clf = LogisticRegression().fit(X_train_preprocessed_features,␣
 ↪y_train_preprocessed)
```

[578]:
```
lr_train_score = clf.score(X_train_preprocessed_features, y_train_preprocessed)
lr_test_score = clf.score(X_test_preprocessed_features, y_test_preprocessed)

print("Train accuracy: ", lr_train_score)
print("Test accuracy: ", lr_test_score)
```

```
Train accuracy:  0.9664705882352941
Test accuracy:  0.9530516431924883
```

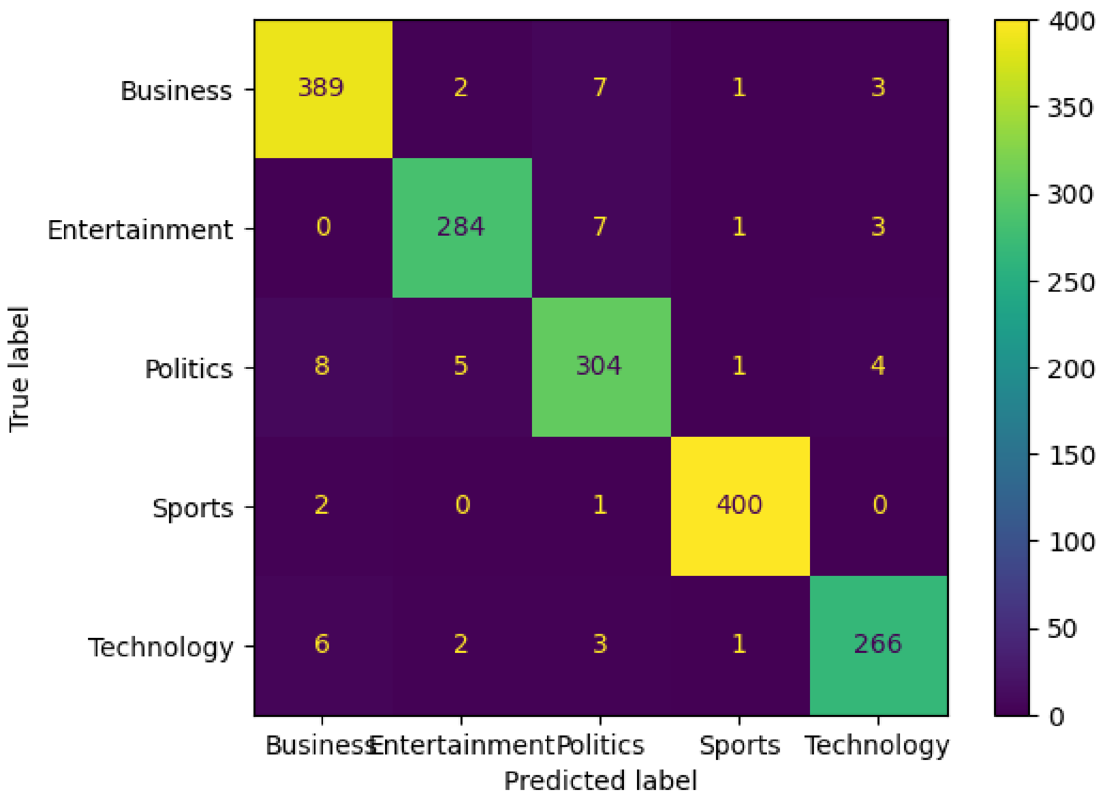
5.4.1 Metrics

[567]:
```
print(classification_report(y_train_preprocessed, clf.
    predict(X_train_preprocessed_features), target_names=category_labels))
```

```
               precision    recall  f1-score   support

     Business       0.96      0.97      0.96       402
Entertainment       0.97      0.96      0.97       295
     Politics       0.94      0.94      0.94       322
       Sports       0.99      0.99      0.99       403
   Technology       0.96      0.96      0.96       278

     accuracy                           0.97      1700
    macro avg       0.97      0.96      0.97      1700
 weighted avg       0.97      0.97      0.97      1700
```

[568]:
```
ConfusionMatrixDisplay(confusion_matrix(y_train_preprocessed, clf.
    predict(X_train_preprocessed_features)),display_labels=label_encoder.
    inverse_transform([0,1,2,3,4])).plot()
```

[568]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2a3c2b674a0>



[569]:

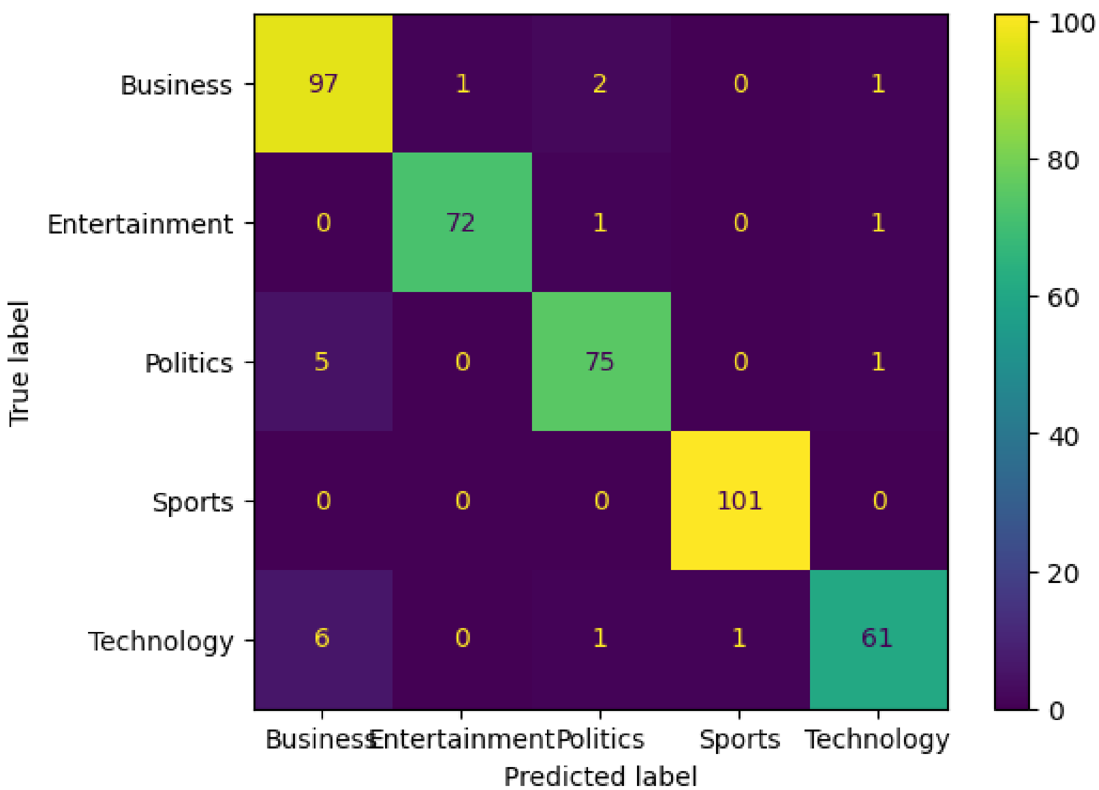
```
print(classification_report(y_test_preprocessed, clf.
↪predict(X_test_preprocessed_features), target_names=category_labels))
```

```
               precision    recall  f1-score   support

     Business       0.90      0.96      0.93       101
Entertainment       0.99      0.97      0.98        74
     Politics       0.95      0.93      0.94        81
       Sports       0.99      1.00      1.00       101
   Technology       0.95      0.88      0.92        69

     accuracy                           0.95       426
    macro avg       0.96      0.95      0.95       426
 weighted avg       0.95      0.95      0.95       426
```

[570]:

```
ConfusionMatrixDisplay(confusion_matrix(y_test_preprocessed, clf.
↪predict(X_test_preprocessed_features)),display_labels=category_labels).plot()
```

[570]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2a3c2b35070>



Observation > This method is providing good accuracy but it is not good method because > 1. Huge memory usage by dictionary > 2. Most words only appear in few categories > 3. Does not consider word importance across multiple documents > 4. no context awareness > 5. poor generalization to new words > 6. common words like "said, news" appear important in all categories > 7. Infrequent but highly informative words get ignored > 8. Not scalable

6 COUNT VECTORIZER AND MODEL TRAINING

6.1 BAG OF WORDS VECTORIZATION

[571]:
```
cv = CountVectorizer(stop_words="english",max_features=5000)
X_train_cv = cv.fit_transform(X_train_preprocessed["Article"]).toarray()
y_train_cv = y_train_preprocessed.values
```

[572]:
```
X_test_cv = cv.transform(X_test_preprocessed["Article"]).toarray()
y_test_cv = y_test_preprocessed.values
```

6.2 TSNE VISUALISATION OF BOW VECTORS

[650]:
```
# Apply t-SNE on X_train_cv
tsne = TSNE(n_components=2, random_state=42)
tsne_features = tsne.fit_transform(X_train_cv)

# Convert to DataFrame
tsne_df = pd.DataFrame(tsne_features, columns=["C1", "C2"])

# Reset index to align with X_train_preprocessed
X_train_preprocessed = X_train_preprocessed.reset_index(drop=True)

# Decode category labels using LabelEncoder
tsne_df["Category"] = label_encoder.inverse_transform(y_train_cv)

# Ensure correct color matching
tsne_df["Category"] = pd.Categorical(tsne_df["Category"],␣
 ↪categories=category_labels, ordered=True)

# for hover purpose - 1st hunderd characters of the article
tsne_df["Article_100"] = X_train_preprocessed["Article"].str[:100]

# Plot t-SNE visualization
fig = px.scatter(tsne_df,
                 x="C1",
                 y="C2",
                 hover_data=["Article_100"],
                 title="t-SNE Visualization of BOW Representation",
                 color="Category")
```

```
fig.show()
```

6.3 SIMPLE NAIVE BAYES CLASSIFIER

[574]:
```
nb = MultinomialNB()
nb.fit(X_train_cv, y_train_cv)
```

[574]: MultinomialNB()

6.3.1 Metrics

[606]:
```
# Get predictions
y_train_pred = nb.predict(X_train_cv)
y_test_pred = nb.predict(X_test_cv)

# Get probability predictions for ROC-AUC calculation
y_train_prob = nb.predict_proba(X_train_cv)
y_test_prob = nb.predict_proba(X_test_cv)

# Compute all metrics
metrics = {
    "Metric": ["Accuracy", "Precision", "Recall", "F1-score", "ROC-AUC"],
    "Train Score": [
        accuracy_score(y_train_cv, y_train_pred),
        precision_score(y_train_cv, y_train_pred, average='weighted'),
        recall_score(y_train_cv, y_train_pred, average='weighted'),
        f1_score(y_train_cv, y_train_pred, average='weighted'),
        roc_auc_score(y_train_cv, y_train_prob, average='weighted',␣
↪multi_class="ovr")  # FIXED
    ],
    "Test Score": [
        accuracy_score(y_test_cv, y_test_pred),
        precision_score(y_test_cv, y_test_pred, average='weighted'),
        recall_score(y_test_cv, y_test_pred, average='weighted'),
        f1_score(y_test_cv, y_test_pred, average='weighted'),
        roc_auc_score(y_test_cv, y_test_prob, average='weighted',␣
↪multi_class="ovr")  # FIXED
    ]
}

# Convert to DataFrame
df_metrics = pd.DataFrame(metrics)

# Print results in a tabular format
print(df_metrics)
```

```
      Metric  Train Score  Test Score
0   Accuracy     0.991176    0.974178
```

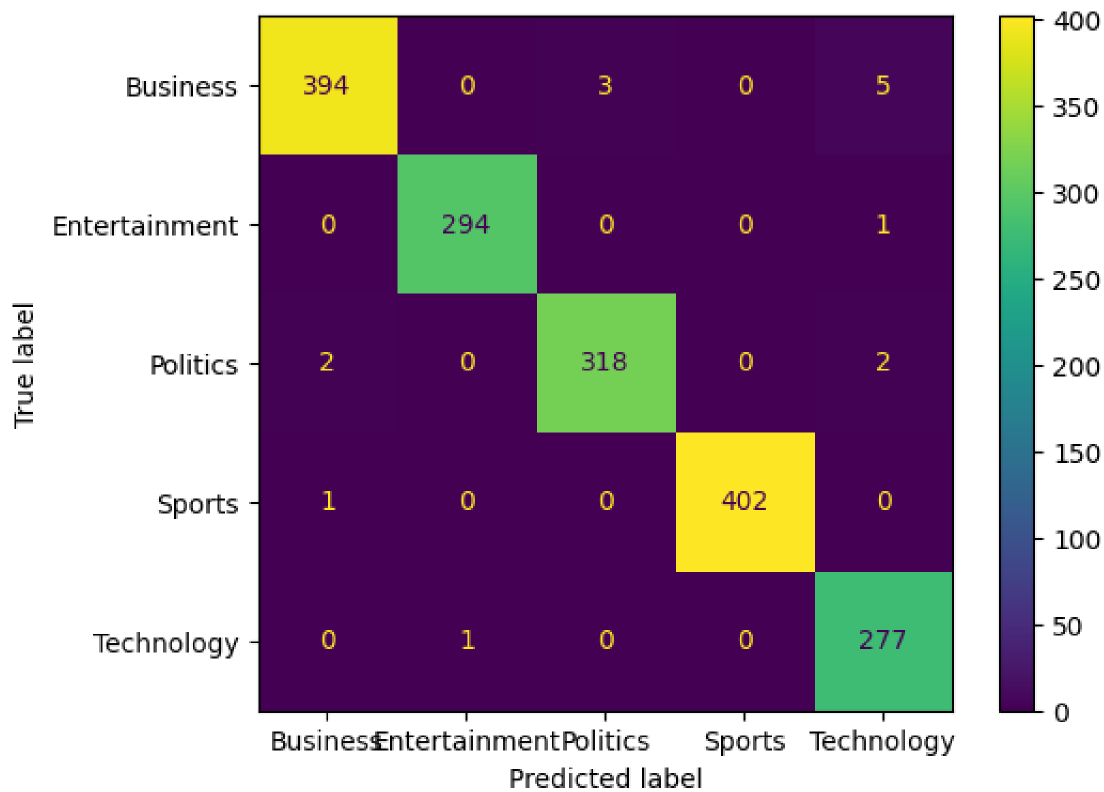
```
1   Precision     0.991264    0.974561
2      Recall     0.991176    0.974178
3    F1-score     0.991186    0.974252
4     ROC-AUC     0.999321    0.998373
```

[579]:
```python
print(classification_report(y_train_cv, nb.predict(X_train_cv),
 ↪target_names=category_labels))
```

```
               precision    recall  f1-score   support

     Business       0.99      0.98      0.99       402
Entertainment       1.00      1.00      1.00       295
     Politics       0.99      0.99      0.99       322
       Sports       1.00      1.00      1.00       403
   Technology       0.97      1.00      0.98       278

     accuracy                           0.99      1700
    macro avg       0.99      0.99      0.99      1700
 weighted avg       0.99      0.99      0.99      1700
```

[582]:
```python
ConfusionMatrixDisplay(confusion_matrix(y_train_cv, nb.
 ↪predict(X_train_cv)),display_labels=category_labels).plot()
```

[582]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2a3c6194fb0>

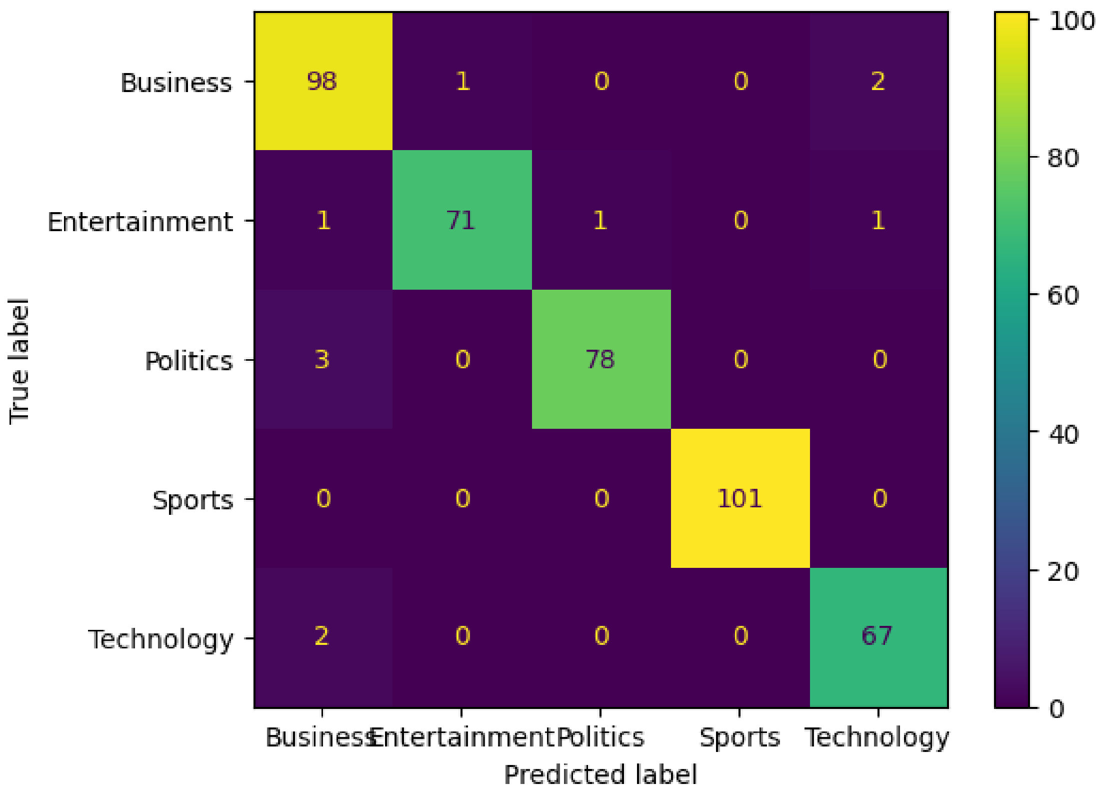


[584]:
```
print(classification_report(y_test_cv, nb.predict(X_test_cv),
    target_names=category_labels))
```

```
               precision    recall  f1-score   support

     Business       0.94      0.97      0.96       101
Entertainment       0.99      0.96      0.97        74
     Politics       0.99      0.96      0.97        81
       Sports       1.00      1.00      1.00       101
   Technology       0.96      0.97      0.96        69

     accuracy                           0.97       426
    macro avg       0.97      0.97      0.97       426
 weighted avg       0.97      0.97      0.97       426
```

[585]:
```
ConfusionMatrixDisplay(confusion_matrix(y_test_cv, nb.
    predict(X_test_cv)),display_labels=category_labels).plot()
```

[585]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2a3c614c7d0>



6.4 FUNCTION FOR ML MODEL TRAINING AND EVALUATION

[691]:
```
def model_training_and_evaluation(model, param_grid, X_train, y_train, X_test,␣
↪y_test, category_labels, run_name, cv=5, n_iter=20):
    # Set the MLflow experiment
    mlflow.set_experiment("news_article_document_classification")

    # Start a new MLflow run with the provided run name
    with mlflow.start_run(run_name=run_name):
        # Perform hyperparameter tuning using RandomizedSearchCV
        search = RandomizedSearchCV(model, param_distributions=param_grid,␣
↪n_iter=n_iter, cv=cv, scoring='accuracy', n_jobs=-1, verbose=1,␣
↪random_state=42)
        search.fit(X_train, y_train)

        # Get the best model after tuning
        best_model = search.best_estimator_
        best_params = search.best_params_

        # Predictions
        y_train_pred = best_model.predict(X_train)
        y_test_pred = best_model.predict(X_test)

        # Probability Predictions for ROC-AUC
        y_train_prob = best_model.predict_proba(X_train)
        y_test_prob = best_model.predict_proba(X_test)

        # Compute training metrics
        train_metrics = {
            "Accuracy": accuracy_score(y_train, y_train_pred),
            "Precision": precision_score(y_train, y_train_pred,␣
↪average='weighted'),
            "Recall": recall_score(y_train, y_train_pred, average='weighted'),
            "F1-score": f1_score(y_train, y_train_pred, average='weighted'),
            "ROC-AUC": roc_auc_score(y_train, y_train_prob, average='weighted',␣
↪multi_class="ovr")
        }

        # Compute testing metrics
        test_metrics = {
            "Accuracy": accuracy_score(y_test, y_test_pred),
            "Precision": precision_score(y_test, y_test_pred,␣
↪average='weighted'),
            "Recall": recall_score(y_test, y_test_pred, average='weighted'),
            "F1-score": f1_score(y_test, y_test_pred, average='weighted'),
```

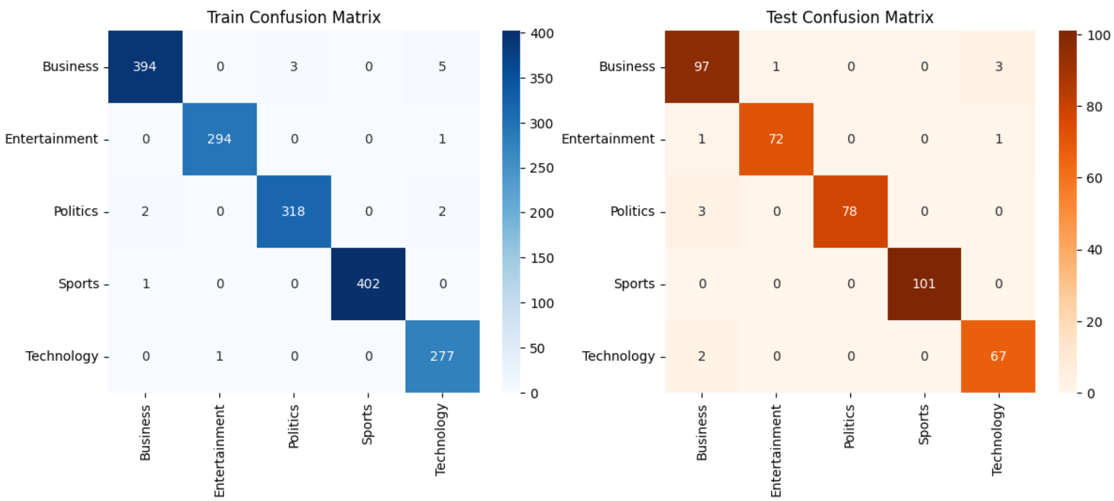
```
            "ROC-AUC": roc_auc_score(y_test, y_test_prob, average='weighted',␣
↪multi_class="ovr")
        }

        # Log model parameters & metrics to MLflow
        mlflow.log_params(best_params)
        mlflow.log_metrics({f"train_{k}": v for k, v in train_metrics.items()})␣
↪ # Log training metrics with 'train_' prefix
        mlflow.log_metrics({f"test_{k}": v for k, v in test_metrics.items()})  ␣
↪ # Log test metrics with 'test_' prefix
        mlflow.sklearn.log_model(best_model, "best_model")

        # Print best hyperparameters
        print("\n Best Hyperparameters:", best_params)

        # Convert metrics to DataFrame for display
        df_train_metrics = pd.DataFrame([train_metrics])
        df_test_metrics = pd.DataFrame([test_metrics])
        print("\n Training Metrics:")
        print(df_train_metrics)

        print("\n Testing Metrics:")
        print(df_test_metrics)

        # Print classification reports
        print("\n Training Classification Report:")
        print(classification_report(y_train, y_train_pred,␣
↪target_names=category_labels))

        print("\n Testing Classification Report:")
        print(classification_report(y_test, y_test_pred,␣
↪target_names=category_labels))

        # Plot Confusion Matrices
        fig, axes = plt.subplots(1, 2, figsize=(14, 5))

        sns.heatmap(confusion_matrix(y_train, y_train_pred), annot=True,␣
↪fmt='d', cmap='Blues', xticklabels=category_labels,␣
↪yticklabels=category_labels, ax=axes[0])
        axes[0].set_title("Train Confusion Matrix")

        sns.heatmap(confusion_matrix(y_test, y_test_pred), annot=True, fmt='d',␣
↪cmap='Oranges', xticklabels=category_labels, yticklabels=category_labels,␣
↪ax=axes[1])
        axes[1].set_title("Test Confusion Matrix")
```

```
        # Save confusion matrix plot as an artifact
        plt.savefig("confusion_matrix.png")
        mlflow.log_artifact("confusion_matrix.png")
        plt.show()

        print("\n Model & Results Logged in MLflow!")

        return best_model  # Return the trained model
```

[695]:
```
nb = MultinomialNB()
param_grid = {"alpha" : [0.1, 0.5, 1.0, 2.0]}
best_nb_cv_model = model_training_and_evaluation(nb, param_grid,X_train_cv,␣
 ↪y_train_cv, X_test_cv, y_test_cv, category_labels,run_name = "MultinomialNB␣
 ↪CV")
```

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits

2025/02/06 23:22:40 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmprgf00tkc\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.


 Best Hyperparameters: {'alpha': 0.5}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.991176   0.991264  0.991176  0.991186  0.999438

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.974178   0.974684  0.974178  0.974304  0.998358

 Training Classification Report:
               precision    recall  f1-score   support

     Business       0.99      0.98      0.99       402
Entertainment       1.00      1.00      1.00       295
     Politics       0.99      0.99      0.99       322
       Sports       1.00      1.00      1.00       403
   Technology       0.97      1.00      0.98       278

     accuracy                           0.99      1700
    macro avg       0.99      0.99      0.99      1700
 weighted avg       0.99      0.99      0.99      1700


 Testing Classification Report:
```

```
               precision    recall  f1-score   support

     Business       0.94      0.96      0.95       101
Entertainment       0.99      0.97      0.98        74
     Politics       1.00      0.96      0.98        81
       Sports       1.00      1.00      1.00       101
   Technology       0.94      0.97      0.96        69

     accuracy                           0.97       426
    macro avg       0.97      0.97      0.97       426
 weighted avg       0.97      0.97      0.97       426
```




```
Model & Results Logged in MLflow!
```

6.5 DECISION TREE CLASSIFIER

[696]:

```
dt = DecisionTreeClassifier(random_state=42)
param_grid = {
    'criterion': ['gini', 'entropy'],  # Function to measure the quality of a␣
 ↪split
    'max_depth': [None, 10, 20, 30, 40, 50],  # The maximum depth of the tree
    'min_samples_split': [2, 5, 10, 20],  # The minimum number of samples␣
 ↪required to split an internal node
    'min_samples_leaf': [1, 2, 4, 10],   # The minimum number of samples␣
 ↪required to be at a leaf node
    'max_leaf_nodes': [None, 10, 20, 30],  # Grow a tree with max_leaf_nodes in␣
 ↪best-first fashion
    'class_weight': ['balanced'],  # Weights associated with classes
```

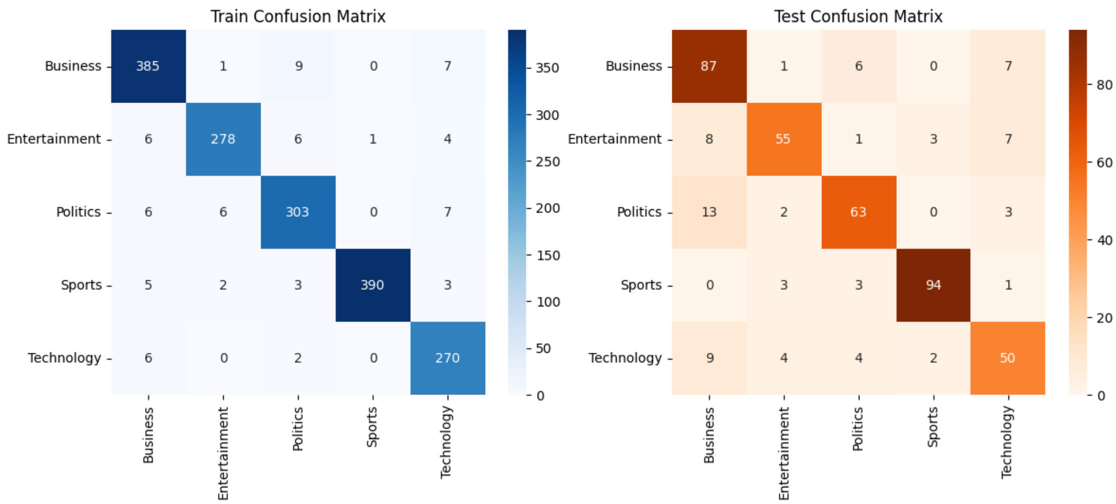
```python
}
best_dt_cv_model = model_training_and_evaluation(dt,param_grid, X_train_cv,
 ↪y_train_cv, X_test_cv, y_test_cv, category_labels,run_name="DecisionTree_CV")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
2025/02/06 23:23:01 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpm5ebxpui\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'min_samples_split': 20, 'min_samples_leaf': 2,
'max_leaf_nodes': None, 'max_depth': 30, 'criterion': 'gini', 'class_weight':
'balanced'}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.956471   0.957092  0.956471  0.956603  0.998481

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.819249   0.823063  0.819249  0.819427  0.918991

 Training Classification Report:
               precision    recall  f1-score   support

     Business       0.94      0.96      0.95       402
Entertainment       0.97      0.94      0.96       295
     Politics       0.94      0.94      0.94       322
       Sports       1.00      0.97      0.98       403
   Technology       0.93      0.97      0.95       278

     accuracy                           0.96      1700
    macro avg       0.96      0.96      0.96      1700
 weighted avg       0.96      0.96      0.96      1700


 Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.74      0.86      0.80       101
Entertainment       0.85      0.74      0.79        74
     Politics       0.82      0.78      0.80        81
       Sports       0.95      0.93      0.94       101
   Technology       0.74      0.72      0.73        69

     accuracy                           0.82       426
```

```
   macro avg       0.82      0.81      0.81       426
weighted avg       0.82      0.82      0.82       426
```




```
Model & Results Logged in MLflow!
```

6.6 NEAREST NEIGHBORS CLASSIFIER

[698]:

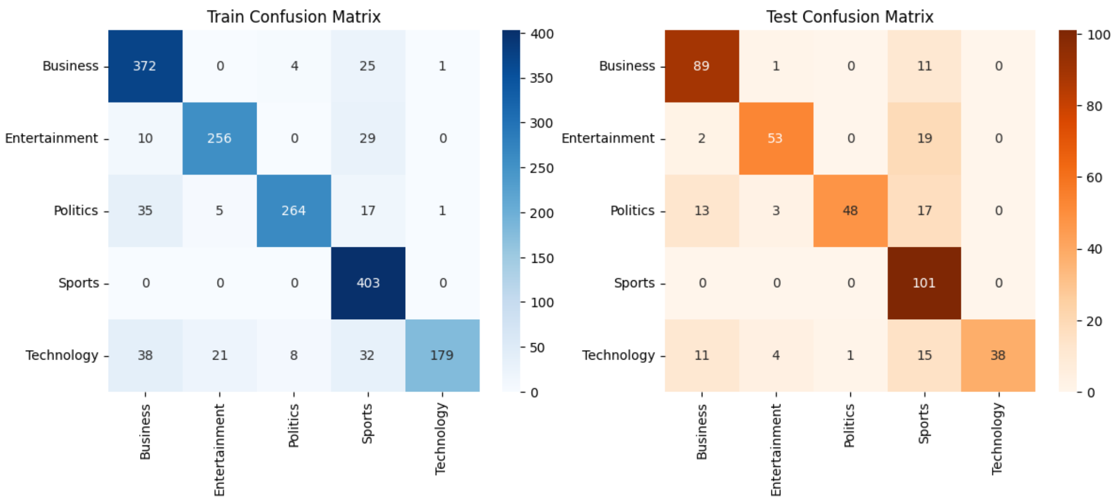
```
knn = KNeighborsClassifier()
param_grid = {
    'n_neighbors': [3, 5, 7, 9, 11, 15, 20],  # The number of neighbors to use␣
 ↪for kneighbors queries
    'p': [1, 2],  # Power parameter for the Minkowski distance
    'metric': ['minkowski', 'euclidean', 'manhattan'],  # Distance metric to use
    'n_jobs': [-1]  # Number of jobs to run in parallel
}
best_knn_cv_model = model_training_and_evaluation(knn, param_grid,X_train_cv,␣
 ↪y_train_cv, X_test_cv, y_test_cv, category_labels,run_name = "KNN_CV")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
2025/02/06 23:26:53 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpk0isdgpa\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'p': 2, 'n_neighbors': 3, 'n_jobs': -1, 'metric':
'euclidean'}
```

```
 Training Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.867059   0.882567  0.867059  0.864255  0.994815

 Testing Metrics:
   Accuracy  Precision  Recall  F1-score   ROC-AUC
0    0.7723   0.829554  0.7723  0.768639  0.928263

 Training Classification Report:
               precision    recall  f1-score   support

     Business       0.82      0.93      0.87       402
Entertainment       0.91      0.87      0.89       295
     Politics       0.96      0.82      0.88       322
       Sports       0.80      1.00      0.89       403
   Technology       0.99      0.64      0.78       278

     accuracy                           0.87      1700
    macro avg       0.89      0.85      0.86      1700
 weighted avg       0.88      0.87      0.86      1700


 Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.77      0.88      0.82       101
Entertainment       0.87      0.72      0.79        74
     Politics       0.98      0.59      0.74        81
       Sports       0.62      1.00      0.77       101
   Technology       1.00      0.55      0.71        69

     accuracy                           0.77       426
    macro avg       0.85      0.75      0.76       426
 weighted avg       0.83      0.77      0.77       426
```




```
Model & Results Logged in MLflow!
```

6.7 RANDOM FOREST CLASSIFIER

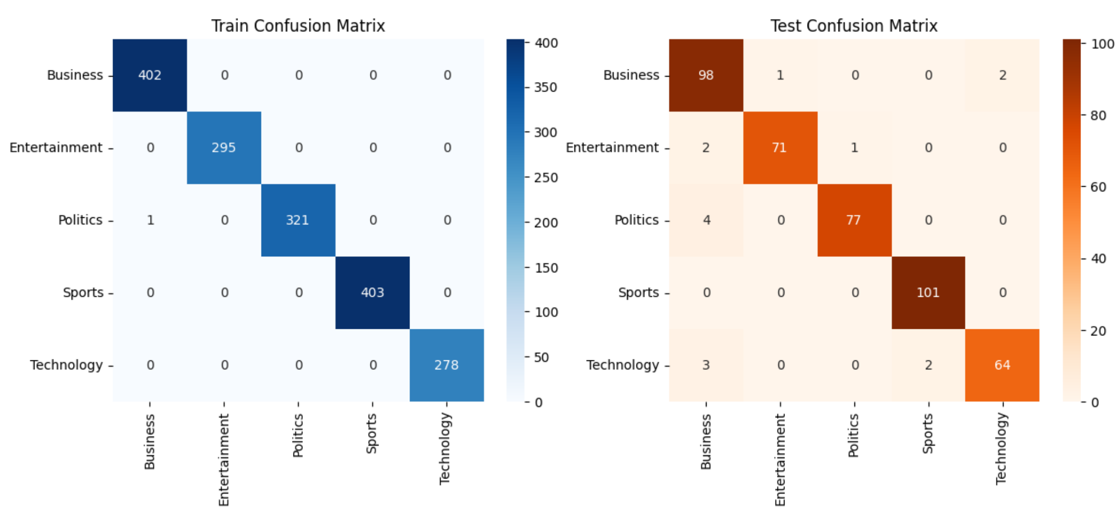
[700]:
```python
rf = RandomForestClassifier()
param_grid ={
    'n_estimators': [50, 100, 150, 200],  # Number of trees in the forest
    'max_depth': [None, 10, 20, 30],  # Maximum depth of the tree
    'min_samples_split': [2, 5, 10],  # Minimum number of samples required to␣
 ↪split an internal node
    'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required to be␣
 ↪at a leaf node
}
best_rf_cv_model = model_training_and_evaluation(rf,param_grid, X_train_cv,␣
 ↪y_train_cv, X_test_cv, y_test_cv, category_labels,cv = 5, n_iter = 20,␣
 ↪run_name="RandomForest_CV")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
2025/02/06 23:31:16 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpwv4p4ryy\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'n_estimators': 150, 'min_samples_split': 5,
'min_samples_leaf': 1, 'max_depth': 20}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score    ROC-AUC
```

```
0  0.999412   0.999413  0.999412  0.999412  0.999994

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.964789   0.965696  0.964789   0.96486  0.998434

 Training Classification Report:
               precision    recall  f1-score   support

     Business       1.00      1.00      1.00       402
Entertainment       1.00      1.00      1.00       295
     Politics       1.00      1.00      1.00       322
       Sports       1.00      1.00      1.00       403
   Technology       1.00      1.00      1.00       278

     accuracy                           1.00      1700
    macro avg       1.00      1.00      1.00      1700
 weighted avg       1.00      1.00      1.00      1700


 Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.92      0.97      0.94       101
Entertainment       0.99      0.96      0.97        74
     Politics       0.99      0.95      0.97        81
       Sports       0.98      1.00      0.99       101
   Technology       0.97      0.93      0.95        69

     accuracy                           0.96       426
    macro avg       0.97      0.96      0.96       426
 weighted avg       0.97      0.96      0.96       426
```



```
Model & Results Logged in MLflow!
```

6.8 GRADIENT BOOSTING CLASSIFIER

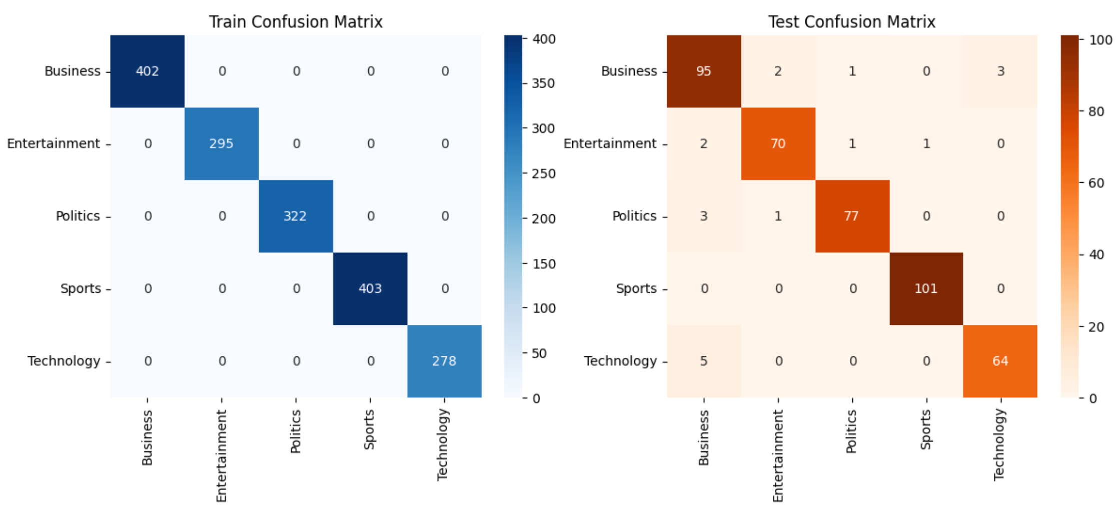
[701]:
```python
gbdt = GradientBoostingClassifier()
param_grid ={
    'n_estimators': [50, 100, 150, 200],  # Number of boosting stages to be run
    'learning_rate': [0.001, 0.01, 0.1, 0.2],  # Step size for each iteration,␣
 ↪trade-off between model complexity and learning speed
    'max_depth': [3, 5, 7, 10],  # Maximum depth of individual trees
    'min_samples_split': [2, 5, 10],  # Minimum number of samples required to␣
 ↪split an internal node
    'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required at a␣
 ↪leaf node
}
best_gbdt_cv_model = model_training_and_evaluation(gbdt,param_grid, X_train_cv,␣
 ↪y_train_cv, X_test_cv, y_test_cv, category_labels,cv = 3, n_iter = 2,␣
 ↪run_name="gbdt_cv")
```

```
Fitting 3 folds for each of 2 candidates, totalling 6 fits
```

```
2025/02/06 23:46:35 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpr621ux3m\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'n_estimators': 200, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_depth': 3, 'learning_rate': 0.2}

 Training Metrics:
   Accuracy  Precision  Recall  F1-score  ROC-AUC
0       1.0        1.0     1.0       1.0      1.0

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.955399   0.955891  0.955399  0.955487  0.998507

 Training Classification Report:
               precision    recall  f1-score   support

     Business       1.00      1.00      1.00       402
Entertainment       1.00      1.00      1.00       295
     Politics       1.00      1.00      1.00       322
```

```
      Sports       1.00      1.00      1.00       403
  Technology       1.00      1.00      1.00       278

    accuracy                           1.00      1700
   macro avg       1.00      1.00      1.00      1700
weighted avg       1.00      1.00      1.00      1700


Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.90      0.94      0.92       101
Entertainment       0.96      0.95      0.95        74
     Politics       0.97      0.95      0.96        81
       Sports       0.99      1.00      1.00       101
   Technology       0.96      0.93      0.94        69

     accuracy                           0.96       426
    macro avg       0.96      0.95      0.95       426
 weighted avg       0.96      0.96      0.96       426
```




```
Model & Results Logged in MLflow!
```

7 UNIGRAM TF_IDF VECTORIZER AND MODEL TRAINING

7.1 UNIGRAM TF_IDF VECTORIZATION

[652]:
```
tf_idf_uni = TfidfVectorizer(stop_words="english",max_features=5000,)
X_train_tf_idf_uni = tf_idf_uni.fit_transform(X_train_preprocessed["Article"]).
 ↪toarray()
y_train_tf_idf_uni = y_train_preprocessed.values
```

[653]:
```
X_test_tf_idf_uni = tf_idf_uni.transform(X_test_preprocessed["Article"]).
 ↪toarray()
y_test_tf_idf_uni = y_test_preprocessed.values
```

7.2 TSNE VISUALISATION OF TF_IDF UNIGRAM VECTORS

[655]:
```
# Apply t-SNE on X_train_tf_idf_uni
tsne = TSNE(n_components=2, random_state=42)
tsne_features = tsne.fit_transform(X_train_tf_idf_uni)

# Convert to DataFrame
tsne_df = pd.DataFrame(tsne_features, columns=["C1", "C2"])

# Reset index to align with X_train_preprocessed
X_train_preprocessed = X_train_preprocessed.reset_index(drop=True)

# Decode category labels using LabelEncoder
tsne_df["Category"] = label_encoder.inverse_transform(y_train_tf_idf_uni)

# Ensure correct color matching
tsne_df["Category"] = pd.Categorical(tsne_df["Category"],␣
 ↪categories=category_labels, ordered=True)

# for hover purpose - 1st hunderd characters of the article
tsne_df["Article_100"] = X_train_preprocessed["Article"].str[:100]

# Plot t-SNE visualization
fig = px.scatter(tsne_df,
                 x="C1",
                 y="C2",
                 hover_data=["Article_100"],
                 title="t-SNE Visualization of TF_IDF_UNIGRAM Representation",
                 color="Category")

fig.show()
```

7.3 SIMPLE NAIVE BAYES CLASSIFIER

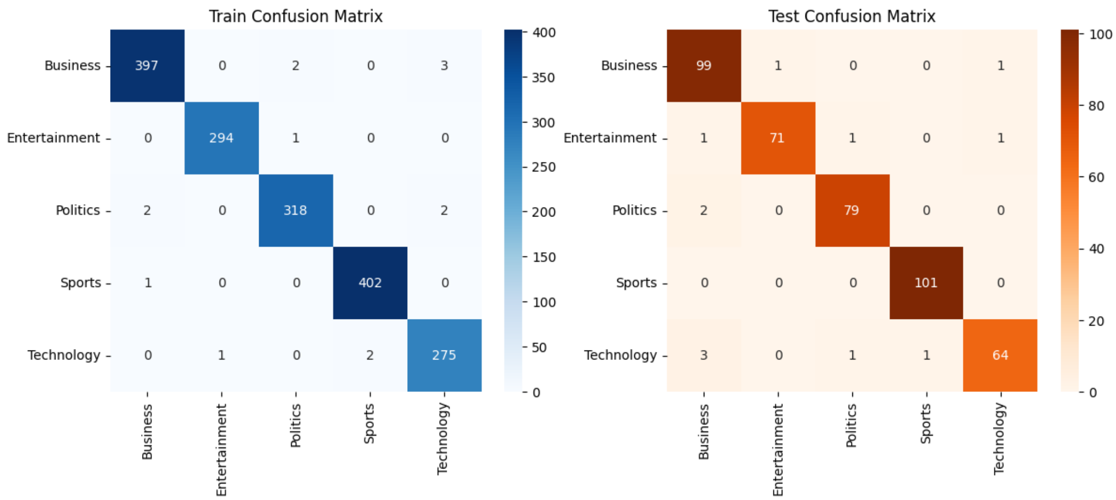
[702]:
```python
nb = MultinomialNB()
param_grid = {"alpha" : [0.1, 0.5, 1.0, 2.0]}
best_nb_tf_idf_uni_model = model_training_and_evaluation(nb,␣
↪param_grid,X_train_tf_idf_uni, y_train_tf_idf_uni, X_test_tf_idf_uni,␣
↪y_test_tf_idf_uni, category_labels,run_name = "MultinomialNB tf_idf_uni")
```

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits
```

```
2025/02/06 23:46:42 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpuy543opb\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'alpha': 0.5}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.991765   0.991774  0.991765  0.991765  0.999795

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.971831   0.972112  0.971831  0.971772  0.999235

 Training Classification Report:
               precision    recall  f1-score   support

     Business       0.99      0.99      0.99       402
Entertainment       1.00      1.00      1.00       295
     Politics       0.99      0.99      0.99       322
       Sports       1.00      1.00      1.00       403
   Technology       0.98      0.99      0.99       278

     accuracy                           0.99      1700
    macro avg       0.99      0.99      0.99      1700
 weighted avg       0.99      0.99      0.99      1700


 Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.94      0.98      0.96       101
Entertainment       0.99      0.96      0.97        74
     Politics       0.98      0.98      0.98        81
       Sports       0.99      1.00      1.00       101
   Technology       0.97      0.93      0.95        69
```

```
    accuracy                           0.97       426
   macro avg       0.97      0.97      0.97       426
weighted avg       0.97      0.97      0.97       426
```




```
Model & Results Logged in MLflow!
```

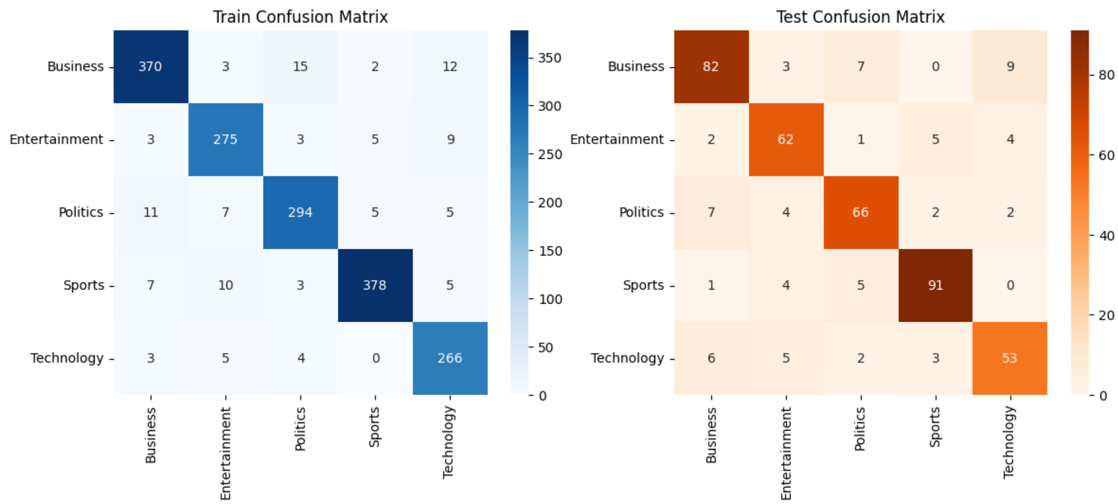
7.4 DECISION TREE CLASSIFIER

[703]:
```python
dt = DecisionTreeClassifier(random_state=42)
param_grid = {
    'criterion': ['gini', 'entropy'],  # Function to measure the quality of a split
    'max_depth': [None, 10, 20, 30, 40, 50],  # The maximum depth of the tree
    'min_samples_split': [2, 5, 10, 20],  # The minimum number of samples required to split an internal node
    'min_samples_leaf': [1, 2, 4, 10],   # The minimum number of samples required to be at a leaf node
    'max_leaf_nodes': [None, 10, 20, 30],  # Grow a tree with max_leaf_nodes in best-first fashion
    'class_weight': ['balanced'],  # Weights associated with classes
}
best_dt_tf_idf_uni_model = model_training_and_evaluation(dt,param_grid, X_train_tf_idf_uni, y_train_tf_idf_uni, X_test_tf_idf_uni, y_test_tf_idf_uni, category_labels,run_name="DecisionTree_tf_idf_uni")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
2025/02/06 23:47:03 WARNING mlflow.utils.environment: Encountered an unexpected
```

```
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpg3_tk6ri\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.


 Best Hyperparameters: {'min_samples_split': 5, 'min_samples_leaf': 4,
'max_leaf_nodes': None, 'max_depth': 40, 'criterion': 'gini', 'class_weight':
'balanced'}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score  ROC-AUC
0  0.931176   0.931928  0.931176  0.931289  0.99692

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.830986   0.831244  0.830986  0.830966  0.922558

 Training Classification Report:
               precision    recall  f1-score   support

     Business       0.94      0.92      0.93       402
Entertainment       0.92      0.93      0.92       295
     Politics       0.92      0.91      0.92       322
       Sports       0.97      0.94      0.95       403
   Technology       0.90      0.96      0.93       278

     accuracy                           0.93      1700
    macro avg       0.93      0.93      0.93      1700
 weighted avg       0.93      0.93      0.93      1700


 Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.84      0.81      0.82       101
Entertainment       0.79      0.84      0.82        74
     Politics       0.81      0.81      0.81        81
       Sports       0.90      0.90      0.90       101
   Technology       0.78      0.77      0.77        69

     accuracy                           0.83       426
    macro avg       0.83      0.83      0.83       426
 weighted avg       0.83      0.83      0.83       426
```




```
Model & Results Logged in MLflow!
```

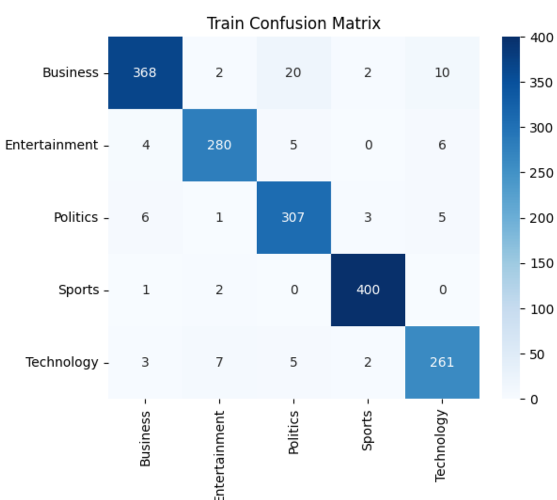
7.5 NEAREST NEIGHBORS CLASSIFIER

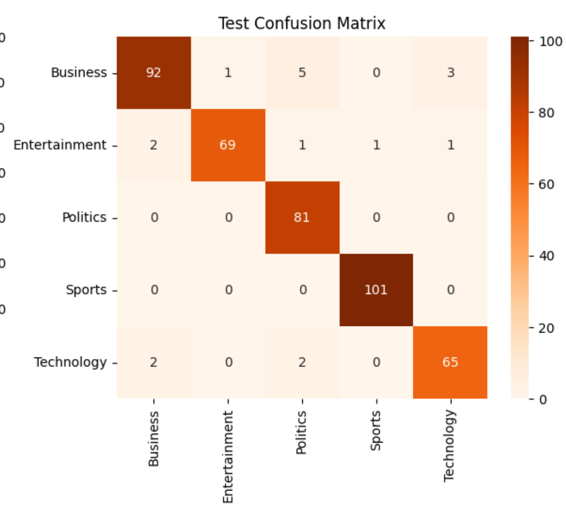
[704]:

```python
knn = KNeighborsClassifier()
param_grid = {
    'n_neighbors': [3, 5, 7, 9, 11, 15, 20],  # The number of neighbors to use␣
 ↪for kneighbors queries
    'p': [1, 2],  # Power parameter for the Minkowski distance
    'metric': ['minkowski', 'euclidean', 'manhattan'],  # Distance metric to use
    'n_jobs': [-1]  # Number of jobs to run in parallel
}
best_knn_tf_idf_uni_model = model_training_and_evaluation(knn,␣
 ↪param_grid,X_train_tf_idf_uni, y_train_tf_idf_uni, X_test_tf_idf_uni,␣
 ↪y_test_tf_idf_uni, category_labels,run_name = "KNN_tf_idf_uni")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits

2025/02/06 23:47:38 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpdaiqcu1m\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.


 Best Hyperparameters: {'p': 2, 'n_neighbors': 20, 'n_jobs': -1, 'metric':
'minkowski'}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.950588   0.951086  0.950588  0.950583  0.996829
```

```
 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.957746   0.958834  0.957746  0.957611  0.998362

 Training Classification Report:
               precision    recall  f1-score   support

     Business       0.96      0.92      0.94       402
Entertainment       0.96      0.95      0.95       295
     Politics       0.91      0.95      0.93       322
       Sports       0.98      0.99      0.99       403
   Technology       0.93      0.94      0.93       278

     accuracy                           0.95      1700
    macro avg       0.95      0.95      0.95      1700
 weighted avg       0.95      0.95      0.95      1700


 Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.96      0.91      0.93       101
Entertainment       0.99      0.93      0.96        74
     Politics       0.91      1.00      0.95        81
       Sports       0.99      1.00      1.00       101
   Technology       0.94      0.94      0.94        69

     accuracy                           0.96       426
    macro avg       0.96      0.96      0.96       426
 weighted avg       0.96      0.96      0.96       426
```





```
Model & Results Logged in MLflow!
```

7.6 RANDOM FOREST CLASSIFIER

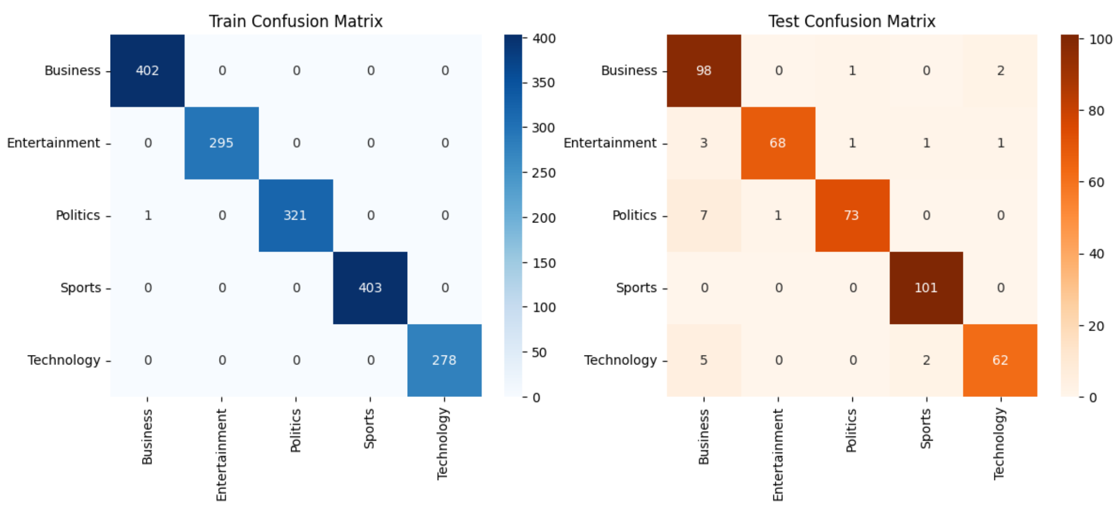
[705]:
```python
rf = RandomForestClassifier()
param_grid ={
    'n_estimators': [50, 100, 150, 200],  # Number of trees in the forest
    'max_depth': [None, 10, 20, 30],  # Maximum depth of the tree
    'min_samples_split': [2, 5, 10],  # Minimum number of samples required to␣
 ↪split an internal node
    'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required to be␣
 ↪at a leaf node
}
best_rf_tf_idf_uni_model = model_training_and_evaluation(rf,param_grid,␣
 ↪X_train_tf_idf_uni, y_train_tf_idf_uni, X_test_tf_idf_uni,␣
 ↪y_test_tf_idf_uni, category_labels,cv = 5, n_iter = 20,␣
 ↪run_name="RandomForest_tf_idf_uni")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
2025/02/06 23:48:17 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpbi1lhkzg\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'n_estimators': 100, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_depth': 20}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.999412   0.999413  0.999412  0.999412  0.999998

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.943662   0.946625  0.943662  0.943809  0.998266

 Training Classification Report:
               precision    recall  f1-score   support

     Business       1.00      1.00      1.00       402
Entertainment       1.00      1.00      1.00       295
     Politics       1.00      1.00      1.00       322
       Sports       1.00      1.00      1.00       403
```

```
  Technology       1.00      1.00      1.00       278

    accuracy                           1.00      1700
   macro avg       1.00      1.00      1.00      1700
weighted avg       1.00      1.00      1.00      1700


Testing Classification Report:
              precision    recall  f1-score   support

    Business       0.87      0.97      0.92       101
Entertainment      0.99      0.92      0.95        74
    Politics       0.97      0.90      0.94        81
      Sports       0.97      1.00      0.99       101
  Technology       0.95      0.90      0.93        69

    accuracy                           0.94       426
   macro avg       0.95      0.94      0.94       426
weighted avg       0.95      0.94      0.94       426
```




```
Model & Results Logged in MLflow!
```

7.7 GRADIENT BOOSTING CLASSIFIER

[706]:
```
gbdt = GradientBoostingClassifier()
param_grid ={
    'n_estimators': [50, 100, 150, 200],  # Number of boosting stages to be run
    'learning_rate': [0.001, 0.01, 0.1, 0.2],  # Step size for each iteration,␣
↪trade-off between model complexity and learning speed
```

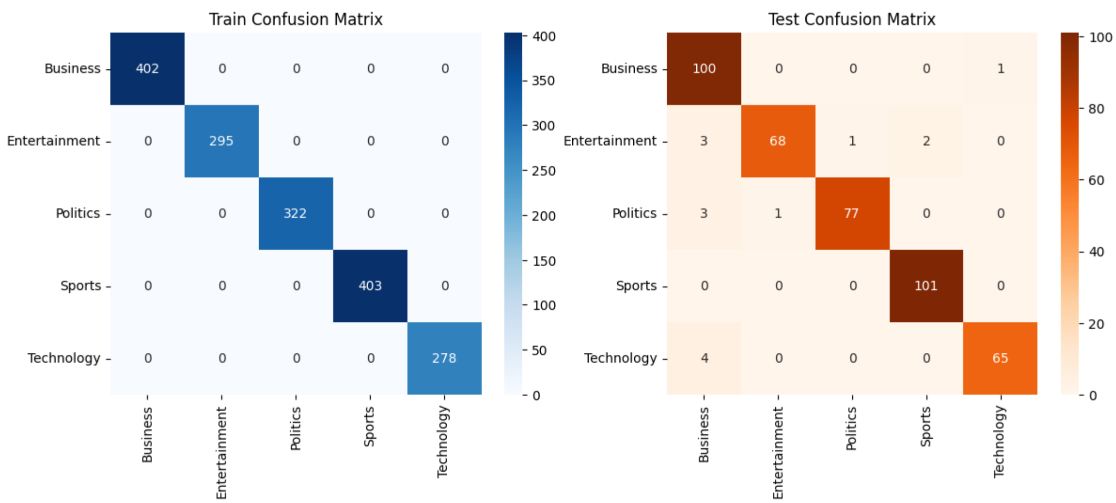
```
    'max_depth': [3, 5, 7, 10],  # Maximum depth of individual trees
    'min_samples_split': [2, 5, 10],  # Minimum number of samples required to␣
 ↪split an internal node
    'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required at a␣
 ↪leaf node
}
best_gbdt_tf_idf_uni_model = model_training_and_evaluation(gbdt,param_grid,␣
 ↪X_train_tf_idf_uni, y_train_tf_idf_uni, X_test_tf_idf_uni,␣
 ↪y_test_tf_idf_uni, category_labels,cv = 3, n_iter = 2,␣
 ↪run_name="gbdt_tf_idf_uni")
```

```
Fitting 3 folds for each of 2 candidates, totalling 6 fits
```

```
2025/02/07 00:03:09 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmptjc3qv2p\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'n_estimators': 200, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_depth': 3, 'learning_rate': 0.2}

 Training Metrics:
   Accuracy  Precision  Recall  F1-score  ROC-AUC
0       1.0        1.0     1.0       1.0      1.0

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.964789   0.966433  0.964789  0.964834  0.998197

 Training Classification Report:
               precision    recall  f1-score   support

     Business       1.00      1.00      1.00       402
Entertainment       1.00      1.00      1.00       295
     Politics       1.00      1.00      1.00       322
       Sports       1.00      1.00      1.00       403
   Technology       1.00      1.00      1.00       278

     accuracy                           1.00      1700
    macro avg       1.00      1.00      1.00      1700
 weighted avg       1.00      1.00      1.00      1700


 Testing Classification Report:
               precision    recall  f1-score   support
```

```
     Business       0.91      0.99      0.95       101
Entertainment       0.99      0.92      0.95        74
     Politics       0.99      0.95      0.97        81
       Sports       0.98      1.00      0.99       101
   Technology       0.98      0.94      0.96        69

     accuracy                           0.96       426
    macro avg       0.97      0.96      0.96       426
 weighted avg       0.97      0.96      0.96       426
```




```
Model & Results Logged in MLflow!
```

8 BIGRAM TF_IDF VECTORIZER AND MODEL TRAINING

8.1 UNIGRAM TF_IDF VECTORIZATION

[707]:
```python
tf_idf_bi = TfidfVectorizer(stop_words="english",max_features=5000,ngram_range=(1,2))
X_train_tf_idf_bi = tf_idf_bi.fit_transform(X_train_preprocessed["Article"]).toarray()
y_train_tf_idf_bi = y_train_preprocessed.values
```

[708]:
```python
X_test_tf_idf_bi = tf_idf_bi.transform(X_test_preprocessed["Article"]).toarray()
y_test_tf_idf_bi = y_test_preprocessed.values
```

8.2 TSNE VISUALISATION OF TF_IDF BIGRAM VECTORS

[709]:
```
# Apply t-SNE on X_train_tf_idf_bi
tsne = TSNE(n_components=2, random_state=42)
tsne_features = tsne.fit_transform(X_train_tf_idf_bi)

# Convert to DataFrame
tsne_df = pd.DataFrame(tsne_features, columns=["C1", "C2"])

# Reset index to align with X_train_preprocessed
X_train_preprocessed = X_train_preprocessed.reset_index(drop=True)

# Decode category labels using LabelEncoder
tsne_df["Category"] = label_encoder.inverse_transform(y_train_tf_idf_bi)

# Ensure correct color matching
tsne_df["Category"] = pd.Categorical(tsne_df["Category"],␣
 ↪categories=category_labels, ordered=True)

# for hover purpose - 1st hunderd characters of the article
tsne_df["Article_100"] = X_train_preprocessed["Article"].str[:100]

# Plot t-SNE visualization
fig = px.scatter(tsne_df,
                 x="C1",
                 y="C2",
                 hover_data=["Article_100"],
                 title="t-SNE Visualization of TF_IDF_biGRAM Representation",
                 color="Category")

fig.show()
```

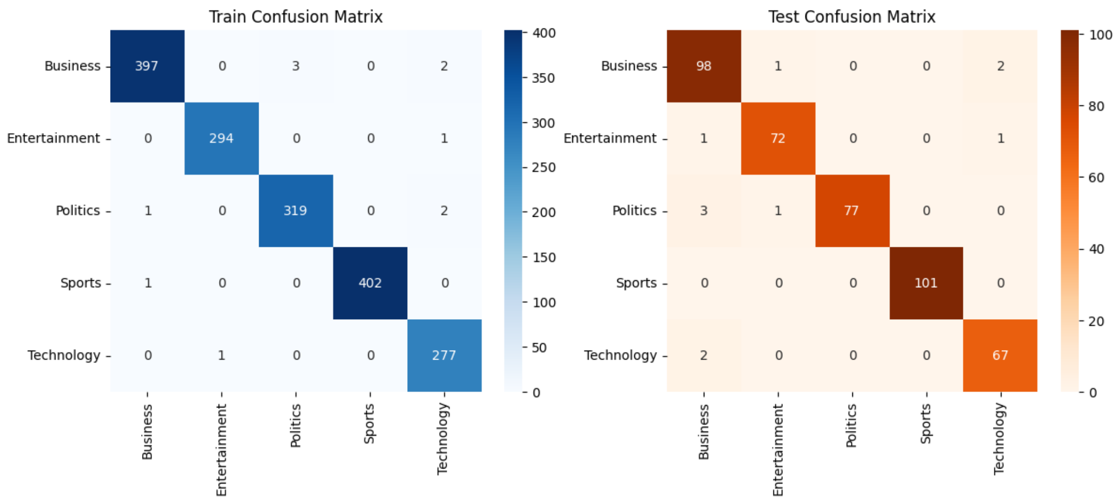
8.3 SIMPLE NAIVE BAYES CLASSIFIER

[710]:
```
nb = MultinomialNB()
param_grid = {"alpha" : [0.1, 0.5, 1.0, 2.0]}
best_nb_tf_idf_bi_model = model_training_and_evaluation(nb,␣
 ↪param_grid,X_train_tf_idf_bi, y_train_tf_idf_bi, X_test_tf_idf_bi,␣
 ↪y_test_tf_idf_bi, category_labels,run_name = "MultinomialNB tf_idf_bi")
```

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits
```

```
2025/02/07 00:03:34 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpxzm0h3r6\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'alpha': 0.1}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.993529   0.993562  0.993529  0.993534  0.999886

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.974178   0.974685  0.974178  0.974256  0.999336

 Training Classification Report:
               precision    recall  f1-score   support

     Business       0.99      0.99      0.99       402
Entertainment       1.00      1.00      1.00       295
     Politics       0.99      0.99      0.99       322
       Sports       1.00      1.00      1.00       403
   Technology       0.98      1.00      0.99       278

     accuracy                           0.99      1700
    macro avg       0.99      0.99      0.99      1700
 weighted avg       0.99      0.99      0.99      1700


 Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.94      0.97      0.96       101
Entertainment       0.97      0.97      0.97        74
     Politics       1.00      0.95      0.97        81
       Sports       1.00      1.00      1.00       101
   Technology       0.96      0.97      0.96        69

     accuracy                           0.97       426
    macro avg       0.97      0.97      0.97       426
 weighted avg       0.97      0.97      0.97       426
```




```
 Model & Results Logged in MLflow!
```

8.4 DECISION TREE CLASSIFIER

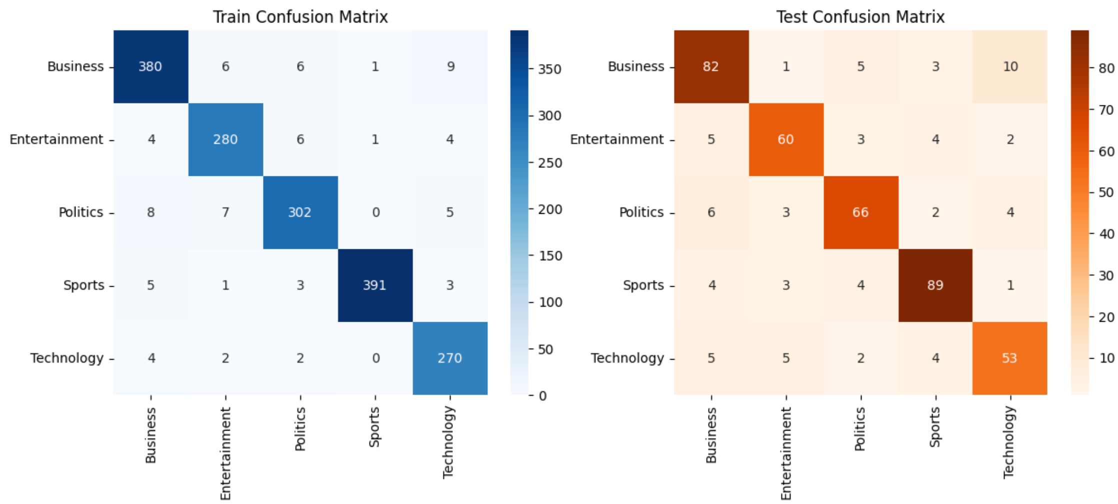
[711]:
```
dt = DecisionTreeClassifier(random_state=42)
param_grid = {
    'criterion': ['gini', 'entropy'],  # Function to measure the quality of a␣
 ↪split
    'max_depth': [None, 10, 20, 30, 40, 50],  # The maximum depth of the tree
    'min_samples_split': [2, 5, 10, 20],  # The minimum number of samples␣
 ↪required to split an internal node
    'min_samples_leaf': [1, 2, 4, 10],   # The minimum number of samples␣
 ↪required to be at a leaf node
    'max_leaf_nodes': [None, 10, 20, 30],  # Grow a tree with max_leaf_nodes in␣
 ↪best-first fashion
    'class_weight': ['balanced'],  # Weights associated with classes
}
best_dt_tf_idf_bi_model = model_training_and_evaluation(dt,param_grid,␣
 ↪X_train_tf_idf_bi, y_train_tf_idf_bi, X_test_tf_idf_bi, y_test_tf_idf_bi,␣
 ↪category_labels,run_name="DecisionTree_tf_idf_bi")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
2025/02/07 00:03:54 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmpgmzqenoy\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'min_samples_split': 20, 'min_samples_leaf': 2,
```

```
'max_leaf_nodes': None, 'max_depth': 30, 'criterion': 'gini', 'class_weight':
'balanced'}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score  ROC-AUC
0  0.954706   0.955135  0.954706  0.954798  0.99839

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.821596   0.821733  0.821596  0.821615  0.921615

 Training Classification Report:
               precision    recall  f1-score   support

     Business       0.95      0.95      0.95       402
Entertainment       0.95      0.95      0.95       295
     Politics       0.95      0.94      0.94       322
       Sports       0.99      0.97      0.98       403
   Technology       0.93      0.97      0.95       278

     accuracy                           0.95      1700
    macro avg       0.95      0.95      0.95      1700
 weighted avg       0.96      0.95      0.95      1700


 Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.80      0.81      0.81       101
Entertainment       0.83      0.81      0.82        74
     Politics       0.82      0.81      0.82        81
       Sports       0.87      0.88      0.88       101
   Technology       0.76      0.77      0.76        69

     accuracy                           0.82       426
    macro avg       0.82      0.82      0.82       426
 weighted avg       0.82      0.82      0.82       426
```




```
Model & Results Logged in MLflow!
```

8.5 NEAREST NEIGHBORS CLASSIFIER

[712]:
```python
knn = KNeighborsClassifier()
param_grid = {
    'n_neighbors': [3, 5, 7, 9, 11, 15, 20],  # The number of neighbors to use␣
 ↪for kneighbors queries
    'p': [1, 2],  # Power parameter for the Minkowski distance
    'metric': ['minkowski', 'euclidean', 'manhattan'],  # Distance metric to use
    'n_jobs': [-1]  # Number of jobs to run in parallel
}
best_knn_tf_idf_bi_model = model_training_and_evaluation(knn,␣
 ↪param_grid,X_train_tf_idf_bi, y_train_tf_idf_bi, X_test_tf_idf_bi,␣
 ↪y_test_tf_idf_bi, category_labels,run_name = "KNN_tf_idf_bi")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits

2025/02/07 00:04:25 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmp3qw_3rr4\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.


 Best Hyperparameters: {'p': 2, 'n_neighbors': 20, 'n_jobs': -1, 'metric':
'minkowski'}

 Training Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.955294   0.955582  0.955294  0.955198  0.997112
```

Testing Metrics:

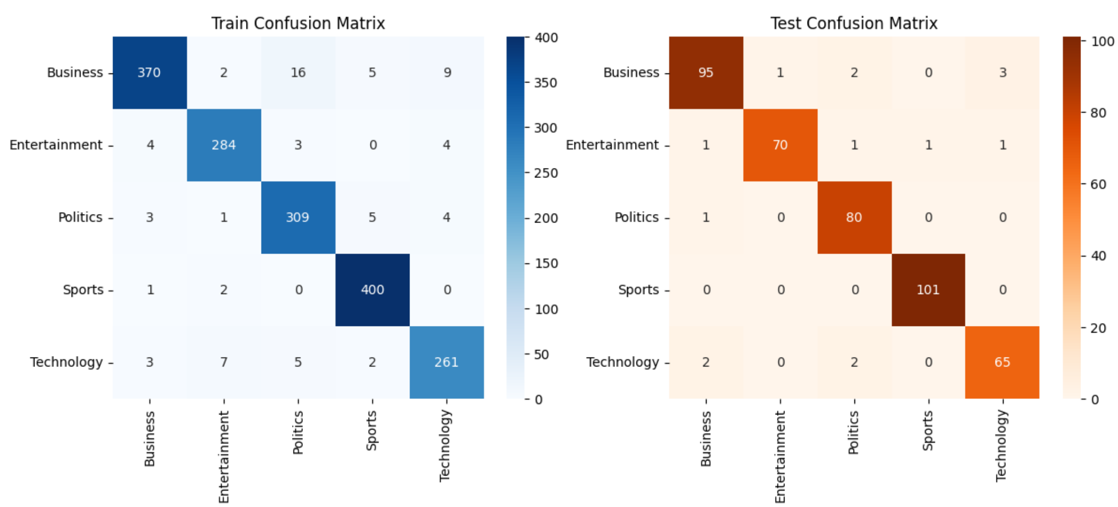
	Accuracy	Precision	Recall	F1-score	ROC-AUC
0	0.964789	0.965075	0.964789	0.964725	0.998474

Training Classification Report:

	precision	recall	f1-score	support
Business	0.97	0.92	0.95	402
Entertainment	0.96	0.96	0.96	295
Politics	0.93	0.96	0.94	322
Sports	0.97	0.99	0.98	403
Technology	0.94	0.94	0.94	278
accuracy			0.96	1700
macro avg	0.95	0.95	0.95	1700
weighted avg	0.96	0.96	0.96	1700

Testing Classification Report:

	precision	recall	f1-score	support
Business	0.96	0.94	0.95	101
Entertainment	0.99	0.95	0.97	74
Politics	0.94	0.99	0.96	81
Sports	0.99	1.00	1.00	101
Technology	0.94	0.94	0.94	69
accuracy			0.96	426
macro avg	0.96	0.96	0.96	426
weighted avg	0.97	0.96	0.96	426



```
Model & Results Logged in MLflow!
```

8.6 RANDOM FOREST CLASSIFIER

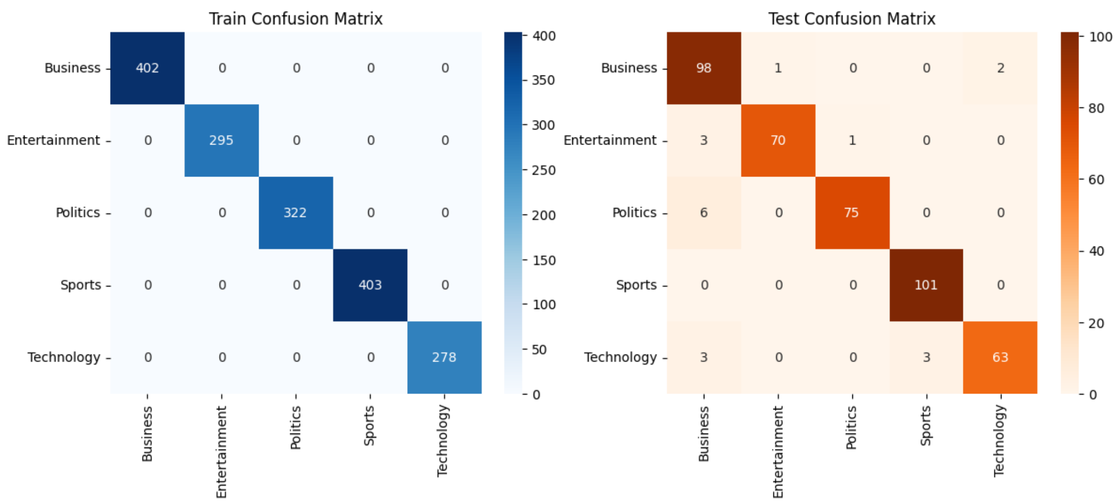
[713]:
```
rf = RandomForestClassifier()
param_grid ={
    'n_estimators': [50, 100, 150, 200],  # Number of trees in the forest
    'max_depth': [None, 10, 20, 30],  # Maximum depth of the tree
    'min_samples_split': [2, 5, 10],  # Minimum number of samples required to␣
 ↪split an internal node
    'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required to be␣
 ↪at a leaf node
}
best_rf_tf_idf_bi_model = model_training_and_evaluation(rf,param_grid,␣
 ↪X_train_tf_idf_bi, y_train_tf_idf_bi, X_test_tf_idf_bi, y_test_tf_idf_bi,␣
 ↪category_labels,cv = 5, n_iter = 20, run_name="RandomForest_tf_idf_bi")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
2025/02/07 00:05:03 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmprz_ybum4\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'n_estimators': 200, 'min_samples_split': 5,
'min_samples_leaf': 2, 'max_depth': None}

 Training Metrics:
   Accuracy  Precision  Recall  F1-score   ROC-AUC
0       1.0        1.0     1.0       1.0  0.999999

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.955399   0.957364  0.955399  0.955538  0.998604

 Training Classification Report:
               precision    recall  f1-score   support

     Business       1.00      1.00      1.00       402
Entertainment       1.00      1.00      1.00       295
     Politics       1.00      1.00      1.00       322
       Sports       1.00      1.00      1.00       403
   Technology       1.00      1.00      1.00       278
```

```
    accuracy                           1.00      1700
   macro avg       1.00      1.00      1.00      1700
weighted avg       1.00      1.00      1.00      1700


Testing Classification Report:
              precision    recall  f1-score   support

     Business       0.89      0.97      0.93       101
Entertainment       0.99      0.95      0.97        74
     Politics       0.99      0.93      0.96        81
       Sports       0.97      1.00      0.99       101
   Technology       0.97      0.91      0.94        69

     accuracy                           0.96       426
    macro avg       0.96      0.95      0.96       426
 weighted avg       0.96      0.96      0.96       426
```




```
Model & Results Logged in MLflow!
```

8.7 GRADIENT BOOSTING CLASSIFIER

[714]:
```
gbdt = GradientBoostingClassifier()
param_grid ={
    'n_estimators': [50, 100, 150, 200],  # Number of boosting stages to be run
    'learning_rate': [0.001, 0.01, 0.1, 0.2],  # Step size for each iteration,␣
↪trade-off between model complexity and learning speed
    'max_depth': [3, 5, 7, 10],  # Maximum depth of individual trees
```

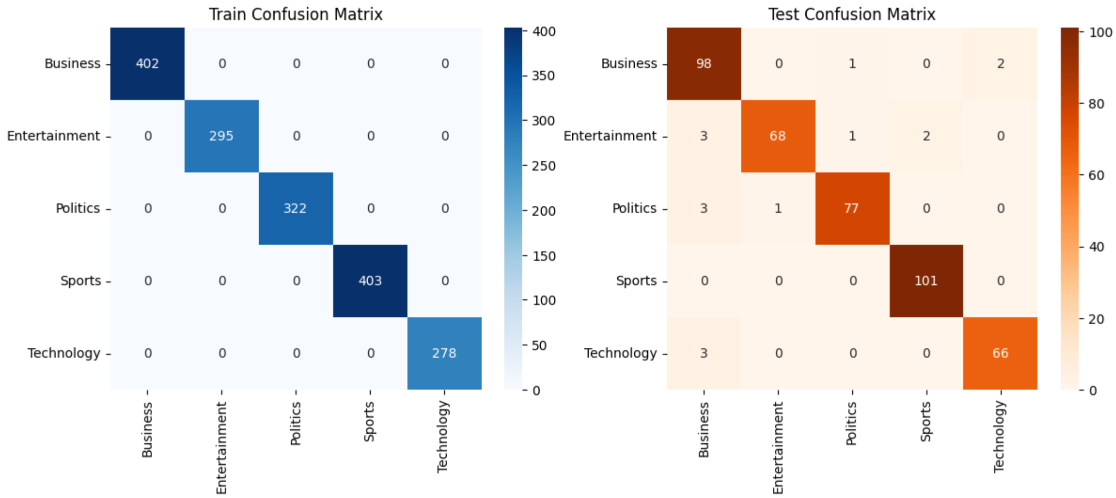
```
    'min_samples_split': [2, 5, 10],  # Minimum number of samples required to␣
↪split an internal node
    'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required at a␣
↪leaf node
}
best_gbdt_tf_idf_bi_model = model_training_and_evaluation(gbdt,param_grid,␣
↪X_train_tf_idf_bi, y_train_tf_idf_bi, X_test_tf_idf_bi, y_test_tf_idf_bi,␣
↪category_labels,cv = 3, n_iter = 2, run_name="gbdt_tf_idf_bi")
```

```
Fitting 3 folds for each of 2 candidates, totalling 6 fits
```

```
2025/02/07 00:19:41 WARNING mlflow.utils.environment: Encountered an unexpected
error while inferring pip requirements (model URI:
C:\Users\saina\AppData\Local\Temp\tmp_as5dipu\model\model.pkl, flavor: sklearn).
Fall back to return ['scikit-learn==1.5.1', 'cloudpickle==3.1.1']. Set logging
level to DEBUG to see the full traceback.
```

```
 Best Hyperparameters: {'n_estimators': 200, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_depth': 3, 'learning_rate': 0.2}

 Training Metrics:
   Accuracy  Precision  Recall  F1-score  ROC-AUC
0       1.0        1.0     1.0       1.0      1.0

 Testing Metrics:
   Accuracy  Precision    Recall  F1-score   ROC-AUC
0  0.962441   0.963359  0.962441  0.962452  0.998126

 Training Classification Report:
               precision    recall  f1-score   support

     Business       1.00      1.00      1.00       402
Entertainment       1.00      1.00      1.00       295
     Politics       1.00      1.00      1.00       322
       Sports       1.00      1.00      1.00       403
   Technology       1.00      1.00      1.00       278

     accuracy                           1.00      1700
    macro avg       1.00      1.00      1.00      1700
 weighted avg       1.00      1.00      1.00      1700


 Testing Classification Report:
               precision    recall  f1-score   support

     Business       0.92      0.97      0.94       101
Entertainment       0.99      0.92      0.95        74
```

```
     Politics       0.97      0.95      0.96        81
       Sports       0.98      1.00      0.99       101
   Technology       0.97      0.96      0.96        69

     accuracy                           0.96       426
    macro avg       0.97      0.96      0.96       426
 weighted avg       0.96      0.96      0.96       426
```




```
Model & Results Logged in MLflow!
```

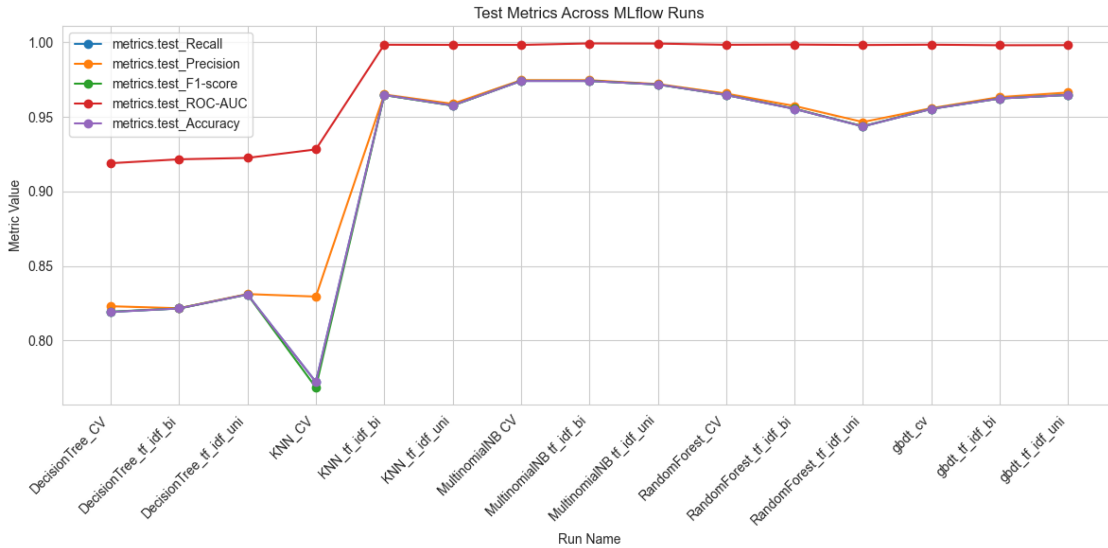
9 PLOTTING THE TEST METRICS FOR COMPARING ALL THE ML MODEL PERFORMANCE

```
[ ]: experiment_name = "news_article_document_classification"  # Replace with your␣
      ↪experiment name
     experiment = mlflow.get_experiment_by_name(experiment_name)

     if experiment is None:
         print(f"Experiment '{experiment_name}' not found.")
         exit()

     # Get all runs
     runs_df = mlflow.search_runs(experiment_ids=[experiment.experiment_id])

     # Get run names separately (for older MLflow versions)
     run_ids = runs_df['run_id'].tolist()
     run_names = []
     for run_id in run_ids:
```

```
    run = mlflow.get_run(run_id)
    run_name = run.info.run_name
    if run_name is None:
        run_name = f"Run ID: {run_id}"
        print(f"Warning: Run {run_id} has no name. Using default.")
    run_names.append(run_name)

runs_df['run_name'] = run_names

# Find correct metric names
correct_metrics = [col for col in runs_df.columns if "test" in col.lower()]
print("Correct metrics found:", correct_metrics)

test_metrics = runs_df[["run_name"] + correct_metrics]

# Convert to numeric, handling errors
for metric in correct_metrics:
    try:
        test_metrics[metric] = pd.to_numeric(test_metrics[metric],␣
 ↪errors='coerce')
    except Exception as e:
        print(f"Error converting metric {metric}: {e}")
        # Handle the error, e.g., drop the column or fill with a value
        # test_metrics.drop(columns=[metric], inplace=True)  # Example: drop␣
 ↪the column

# Handle NaN/inf values
test_metrics.replace([float('inf'), -float('inf')], pd.NA, inplace=True)
test_metrics.dropna(inplace=True)  # Or use fillna() if you prefer

# Order the runs by run_name alphabetically
test_metrics = test_metrics.sort_values(by="run_name")

# Plotting
sns.set_style("whitegrid")
plt.figure(figsize=(12, 6))

for metric in correct_metrics:
    plt.plot(test_metrics["run_name"], test_metrics[metric], marker='o',␣
 ↪label=metric)

plt.xticks(rotation=45, ha="right")
plt.xlabel("Run Name")
plt.ylabel("Metric Value")
plt.title("Test Metrics Across MLflow Runs")
plt.legend()
plt.tight_layout()
```

```
plt.show()
```

```
Correct metrics found: ['metrics.test_Recall', 'metrics.test_Precision',
'metrics.test_F1-score', 'metrics.test_ROC-AUC', 'metrics.test_Accuracy']
```



10 ACTIONABLE INSIGHTS, OBSERVATIONS AND RECOMMENDATIONS

10.0.1 Actionable Insights, Recommendations, and Observations

1. Model Performance Summary

- **Top Performers**:
  - **Random Forest** and **Gradient Boosting** consistently achieved the highest test accuracy (~0.96) and ROC-AUC (~0.998), indicating robust generalization.

  - **Naive Bayes (MultinomialNB)** with TF-IDF also performed exceptionally well (test accuracy ~0.97), offering a simpler yet effective alternative.

- **Underperformers**:
  - **Decision Trees** and **KNN** struggled with overfitting (e.g., Decision Trees: train accuracy ~0.95 vs. test ~0.82).

  - **Logistic Regression** showed moderate performance but was outperformed by ensemble methods.

2. Key Observations

- **TF-IDF Dominates**: Models using TF-IDF vectorization (e.g., Naive Bayes, Random Forest) outperformed Bag-of-Words (BoW), likely due to TF-IDF's ability to weigh term importance across documents.

- **Class Balance**: The dataset's balanced distribution (e.g., Sports: 504, Technology: 347) minimized bias, but slight misclassifications (e.g., Politics vs. Business) suggest targeted improvements.

- **Overfitting in Simpler Models**: Decision Trees and KNN showed significant performance gaps between training and testing, highlighting their unsuitability for this text classification task without regularization.

3. **Recommendations**

- **Deploy Ensemble Models**:
  - Prioritize **Random Forest** or **Gradient Boosting** for deployment due to their high accuracy and stability.

  - Use **Naive Bayes** for scenarios requiring faster inference or lower computational cost.

- **Address Overfitting**:
  - For Decision Trees/KNN: Apply pruning, limit depth, or use ensemble variants (e.g., Bagging) to improve generalization.

- **Optimize Text Representation**:
  - Stick with **TF-IDF** for now, but experiment with advanced embeddings (e.g., BERT, Word2Vec) for potential gains.

- **Monitor and Iterate**:
  - Track model performance post-deployment for concept drift (e.g., evolving news topics).

  - Retrain models periodically with updated data to maintain relevance.

4. **Efficiency and Scalability**

- **Avoid Frequency Dictionaries**: The project noted inefficiencies with manual frequency dictionaries (high memory, poor scalability). TF-IDF or embeddings are better suited.

- **Resource Allocation**: Ensure infrastructure can handle computational demands of ensemble models. Consider model compression (e.g., pruning, quantization) if needed.

5. **Precision vs. Recall Trade-off**

- **Balanced Importance**: Both precision and recall are critical for this use case (as misclassifying news categories could mislead users). The high F1-scores (~0.95–0.97) across top models confirm this balance.

- **Targeted Improvements**: Analyze confusion matrices (e.g., Politics vs. Business errors) to refine feature engineering or gather domain-specific keywords.

6. **Future Directions**
   - **Deep Learning**: Explore transformer-based models (e.g., BERT, RoBERTa) for potential accuracy boosts.
   - **Hyperparameter Tuning**: Use Bayesian Optimization instead of RandomizedSearchCV for faster convergence.
   - **Explainability**: For stakeholder trust, pair high-performing models (Random Forest) with SHAP/LIME interpretations.

---

11 QUESTIONAIRE

11.0.1 Answers to Key Questions

1. **How many news articles are present in the dataset that we have?**
   - The dataset contains **2225** news articles.
2. **Most of the news articles are from ________ category.**
   - Most of the news articles are from the **Sports** category.
3. **Only _____ no. of articles belong to the 'Technology' category.**
   - Only **347** articles belong to the 'Technology' category.
4. **What are Stop Words and why should they be removed from the text data?**
   - **Stop Words** are commonly occurring words such as "the", "is", and "and" that do not add significant meaning to a text. Removing stop words from text data helps reduce noise and enhances computational efficiency, making tasks like text classification and sentiment analysis more effective.
5. **Explain the difference between Stemming and Lemmatization.**
   - **Stemming** reduces words to their root by removing suffixes, often resulting in non-dictionary words (e.g., "running" $\rightarrow$ "run").
   - **Lemmatization** converts words to their base or dictionary form (lemma), ensuring meaningful words as output (e.g., "running" $\rightarrow$ "run"). While lemmatization is more accurate, it is computationally more expensive than stemming.
6. **Which of the techniques Bag of Words or TF-IDF is considered to be more efficient than the other?**
   - **TF-IDF (Term Frequency-Inverse Document Frequency)** is generally more efficient than **Bag of Words (BoW)** because it accounts for word importance in relation to the entire corpus, reducing the influence of commonly occurring words while improving classification performance.
7. **What's the shape of train & test data sets after performing a 75:25 split.**
   - In this analysis, an **80:20 split** was used instead of 75:25. The resulting dataset sizes are:
     - **Training dataset size**: 1700 articles
     - **Testing dataset size**: 426 articles

8. **Which of the following is found to be the best-performing model?**
   - The **Multinomial Naive Bayes** model was found to be the best-performing model. It is preferred due to its **low time complexity** and outstanding performance, achieving **99% accuracy on the training dataset** and **97% accuracy on the test dataset**.
9. **According to this particular use case, both precision and recall are equally important. (T/F)**
   - **True.** Since this use case involves classifying news articles into multiple categories, both precision (correct classification of relevant articles) and recall (ensuring no relevant article is missed) are equally important for balanced performance.
