CSE 5367 – 001 Pattern Recognition

Final Project - Hate Speech Detection

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In [1]:
```
! pip install textstat
! pip install wordcloud
! pip install -U gensim
```

```
Requirement already satisfied: textstat in /Users/Keerthi/anaconda3/li
b/python3.10/site-packages (0.7.3)
Requirement already satisfied: pyphen in /Users/Keerthi/anaconda3/lib/p
ython3.10/site-packages (from textstat) (0.14.0)
Requirement already satisfied: wordcloud in /Users/Keerthi/anaconda3/li
b/python3.10/site-packages (1.9.3)
Requirement already satisfied: numpy>=1.6.1 in /Users/Keerthi/anaconda
3/lib/python3.10/site-packages (from wordcloud) (1.23.5)
Requirement already satisfied: pillow in /Users/Keerthi/anaconda3/lib/p
ython3.10/site-packages (from wordcloud) (9.4.0)
Requirement already satisfied: matplotlib in /Users/Keerthi/anaconda3/l
ib/python3.10/site-packages (from wordcloud) (3.7.0)
Requirement already satisfied: cycler>=0.10 in /Users/Keerthi/anaconda
3/lib/python3.10/site-packages (from matplotlib->wordcloud) (0.11.0)
Requirement already satisfied: pyparsing>=2.3.1 in /Users/Keerthi/anaco
nda3/lib/python3.10/site-packages (from matplotlib->wordcloud) (3.0.9)
Requirement already satisfied: kiwisolver>=1.0.1 in /Users/Keerthi/anac
onda3/lib/python3.10/site-packages (from matplotlib->wordcloud) (1.4.4)
Requirement already satisfied: fonttools>=4.22.0 in /Users/Keerthi/anac
onda3/lib/python3.10/site-packages (from matplotlib->wordcloud) (4.25.
0)
Requirement already satisfied: contourpy>=1.0.1 in /Users/Keerthi/anaco
nda3/lib/python3.10/site-packages (from matplotlib->wordcloud) (1.0.5)
Requirement already satisfied: python-dateutil>=2.7 in /Users/Keerthi/a
naconda3/lib/python3.10/site-packages (from matplotlib->wordcloud) (2.
8.2)
Requirement already satisfied: packaging>=20.0 in /Users/Keerthi/anacon
da3/lib/python3.10/site-packages (from matplotlib->wordcloud) (22.0)
Requirement already satisfied: six>=1.5 in /Users/Keerthi/anaconda3/li
b/python3.10/site-packages (from python-dateutil>=2.7->matplotlib->word
cloud) (1.16.0)
Requirement already satisfied: gensim in /Users/Keerthi/anaconda3/lib/p
ython3.10/site-packages (4.3.2)
Requirement already satisfied: scipy>=1.7.0 in /Users/Keerthi/anaconda
3/lib/python3.10/site-packages (from gensim) (1.10.0)
Requirement already satisfied: numpy>=1.18.5 in /Users/Keerthi/anaconda
3/lib/python3.10/site-packages (from gensim) (1.23.5)
Requirement already satisfied: smart-open>=1.8.1 in /Users/Keerthi/anac
onda3/lib/python3.10/site-packages (from gensim) (5.2.1)
```

In [2]:
```
import re
import numpy as np
import pandas as pd
import seaborn as sns
import scipy

from gensim.models.doc2vec import Doc2Vec, TaggedDocument
from gensim.models.word2vec import Word2Vec

import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.stem.porter import PorterStemmer

from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier

from textstat.textstat import textstat

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.filterwarnings("ignore")

import matplotlib.pyplot as plt
plt.style.use('seaborn-deep')
%matplotlib inline
```

In [3]:
```
dataset = pd.read_csv("HateSpeechData.csv")
dataset
```

Out[3]:

	Unnamed: 0	count	hate_speech	offensive_language	neither	class	tweet
0	0	3	0	0	3	2	!!! RT @mayasolovely: As a woman you shouldn't...
1	1	3	0	3	0	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...
2	2	3	0	3	0	1	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...
3	3	3	0	2	1	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...
4	4	6	0	6	0	1	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...
...	...	...	...	...	...	...	...
24778	25291	3	0	2	1	1	you's a muthaf***in lie “@LifeAsKing: @2...
24779	25292	3	0	1	2	2	you've gone and broke the wrong heart baby, an...
24780	25294	3	0	3	0	1	young buck wanna eat!!.. dat nigguh like I ain...
24781	25295	6	0	6	0	1	youu got wild bitches tellin you lies
24782	25296	3	0	0	3	2	~~Ruffled | Ntac Eileen Dahlia - Beautiful col...

24783 rows × 7 columns

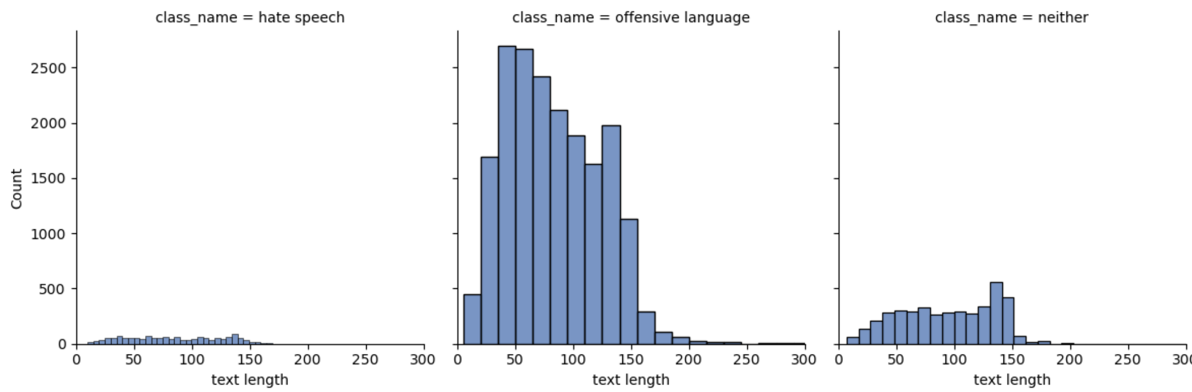
In [4]:
```python
def class_to_name(cls):
    if cls == 0:
        return "hate speech"

    if cls == 1:
        return "offensive language"

    return "neither"


# Adding text length and class name as a field in the dataset
dataset["text length"] = dataset["tweet"].apply(len)
dataset["class_name"] = dataset["class"].apply(class_to_name)

dataset.head()
```

Out[4]:

	Unnamed: 0	count	hate_speech	offensive_language	neither	class	tweet	text length	cl
0	0	3	0	0	3	2	!!! RT @mayasolovely: As a woman you shouldn't...	140	
1	1	3	0	3	0	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...	85	
2	2	3	0	3	0	1	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...	120	
3	3	3	0	2	1	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...	62	
4	4	6	0	6	0	1	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...	137	

In [5]:
```
# Visualizing the dataset using a histogram of text length for each clas
graph = sns.FacetGrid(
    data=dataset,
    col="class_name",
    xlim=[0, 300],
    height=4,
    col_order=["hate speech", "offensive language", "neither"],
)
graph.map(sns.histplot, "text length", bins=50)
```

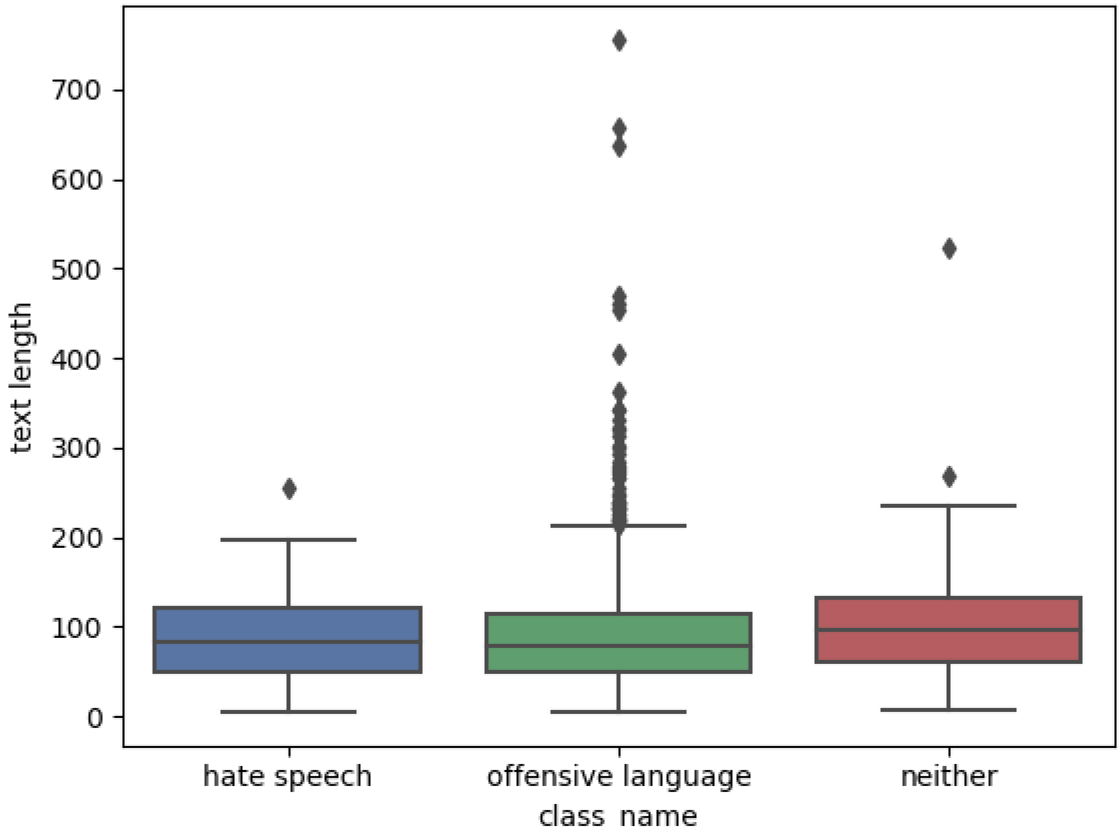
Out[5]:
```
<seaborn.axisgrid.FacetGrid at 0x134ae1030>
```



The distribution of text length appears similar for all three classes. However, the number of offensive tweets is significantly higher.

In [6]:
```
sns.boxplot(
    x="class_name",
    y="text length",
    data=dataset,
    order=["hate speech", "offensive language", "neither"],
)
```

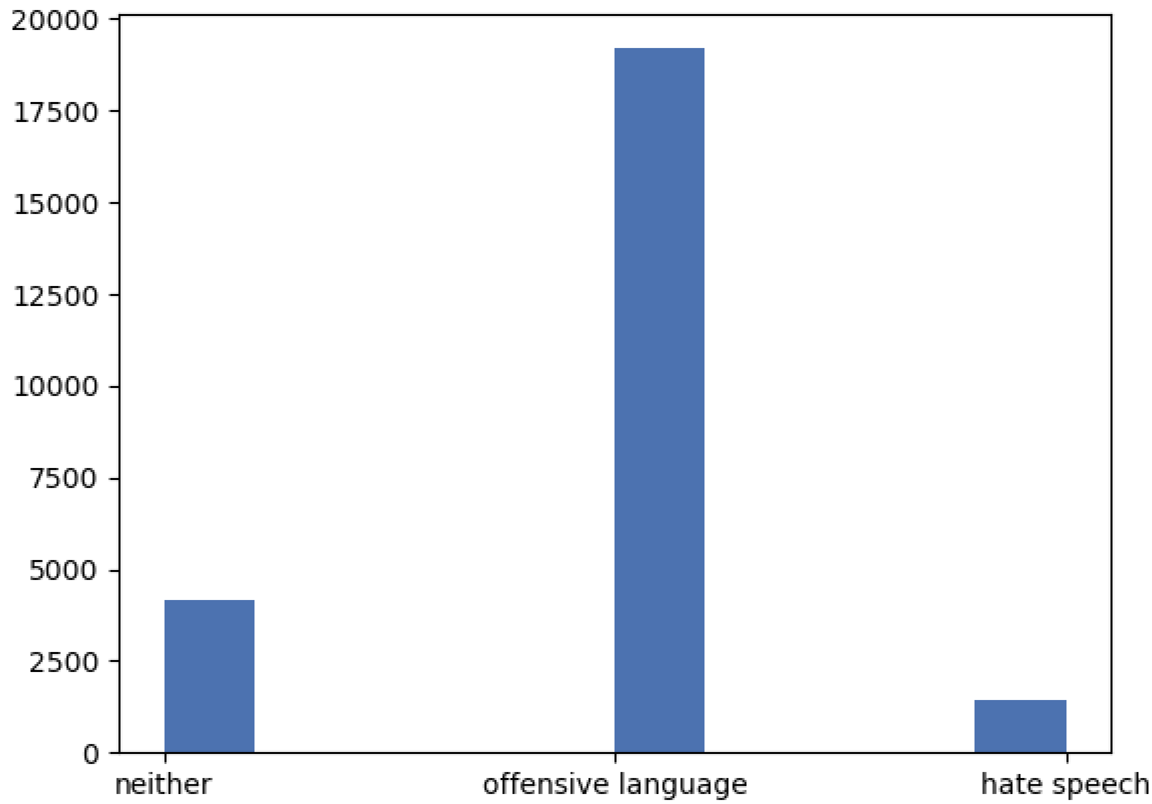
Out[6]: <Axes: xlabel='class_name', ylabel='text length'>



Upon examining the plot, it appears that tweets containing offensive language have longer text length.

In [7]:
```
dataset["class_name"].hist(grid=False)
```

Out[7]: <Axes: >



The above histogram shows that most of the tweets are considered to be offensive.

In [8]:
```
tweet = dataset.tweet
```

Preprocessing the dataset

In [9]:
```
# Download necessary NLTK resources
nltk.download("stopwords")

# Set stopwords
stopwords = nltk.corpus.stopwords.words("english")
# extending the stopwords to include other words used in twitter such as
stopwords.extend(["#ff", "ff", "rt"])

stemmer = PorterStemmer()


def preprocess(tweet):
    # Define patterns to remove URLs, mentions, non-letters, and numbers
    url_pattern = re.compile(r"http[s]?://\S+")
    mention_pattern = re.compile(r"@\w+")
    non_letter_pattern = re.compile(r"[^a-zA-Z\s]")
    number_pattern = re.compile(r"\d+(\.\d+)?")

    # Remove @mentions, URLs, non-letters, and numbers; convert to lowerc
    processed_tweets = (
        tweet.str.replace(url_pattern, "", regex=True)
        .str.replace(mention_pattern, "", regex=True)
        .str.replace(non_letter_pattern, " ", regex=True)
        .str.replace(number_pattern, "numbr", regex=True)
        .str.lower()
        .str.strip()
        .str.split()
    )

    # Remove stopwords and apply stemming
    processed_tweets = processed_tweets.apply(
        lambda tokens: " ".join(
            stemmer.stem(token) for token in tokens if token not in stopw
        )
    )

    return processed_tweets


processed_tweets = preprocess(tweet)

dataset["processed_tweets"] = processed_tweets
dataset[["tweet", "processed_tweets"]].head(10)
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/Keerthi/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[9]:

	tweet	processed_tweets
0	!!! RT @mayasolovely: As a woman you shouldn't...	woman complain clean hous amp man alway take t...
1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...	boy dat cold tyga dwn bad cuffin dat hoe st place
2	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...	dawg ever fuck bitch start cri confus shit
3	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...	look like tranni
4	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...	shit hear might true might faker bitch told ya
5	!!!!!!!!!!!!!!!!!!"@T_Madison_x: The shit just...	shit blow claim faith somebodi still fuck hoe
6	!!!!!!"@__BrighterDays: I can not just sit up ...	sit hate anoth bitch got much shit go
7	!!!!“@selfiequeenbri: cause I'm tired of...	caus tire big bitch come us skinni girl
8	" & you might not get ya bitch back & ...	amp might get ya bitch back amp that
9	" @rhythmixx_ :hobbies include: fighting Maria...	hobbi includ fight mariam bitch

In [10]:
```
# Train a logistic regression model on the provided training data
# and evaluates its performance on the test data.
def logistic_regression_evaluation(X_train, X_test, y_train, y_test):
    lg_model = LogisticRegression()

    lg_model.fit(X_train, y_train)
    y_pred = lg_model.predict(X_test)

    report = classification_report(y_test, y_pred)
    accuracy = accuracy_score(y_test, y_pred)

    return y_pred, report, accuracy


# Train a random forest model on the provided training data
# and evaluates its performance on the test data.
def random_forest_evaluation(X_train, X_test, y_train, y_test):
    random_forest_model = RandomForestClassifier()

    random_forest_model.fit(X_train, y_train)
    y_pred = random_forest_model.predict(X_test)

    report = classification_report(y_test, y_pred)
    accuracy = accuracy_score(y_test, y_pred)

    return y_pred, report, accuracy


# Train a Gaussian Naive Bayes model on the provided training data
# and evaluates its performance on the test data.
def gaussian_nb_evaluation(X_train, X_test, y_train, y_test):
    gaussian_nb_model = GaussianNB()

    if type(X_train) == scipy.sparse._csr.csr_matrix:
        X_train = X_train.toarray()
        X_test = X_test.toarray()

    gaussian_nb_model.fit(X_train, y_train)
    y_pred = gaussian_nb_model.predict(X_test)

    report = classification_report(y_test, y_pred)
    accuracy = accuracy_score(y_test, y_pred)

    return y_pred, report, accuracy


# Train a linear SVC model on the provided training data
# and evaluates its performance on the test data.
def linear_svc_evaluation(X_train, X_test, y_train, y_test):
    linear_svc_model = LinearSVC(random_state=20)

    linear_svc_model.fit(X_train, y_train)
    y_pred = linear_svc_model.predict(X_test)

    report = classification_report(y_test, y_pred)
    accuracy = accuracy_score(y_test, y_pred)
```

```
    return y_pred, report, accuracy


# Train an AdaBoost model on the provided training data
# and evaluates its performance on the test data.
def adaboost_evaluation(X_train, X_test, y_train, y_test):
    adaboost_model = AdaBoostClassifier(
        base_estimator=DecisionTreeClassifier(max_depth=1),
        n_estimators=100,
        learning_rate=1.0,
        random_state=42,
    )

    adaboost_model.fit(X_train, y_train)
    y_pred = adaboost_model.predict(X_test)

    report = classification_report(y_test, y_pred)
    accuracy = accuracy_score(y_test, y_pred)

    return y_pred, report, accuracy


# Evaluate the performance of the models on the provided dataset
def evaluate_models(X_train, X_test, y_train, y_test):
    _, lr_report, lr_accuracy = logistic_regression_evaluation(
        X_train, X_test, y_train, y_test
    )
    _, rf_report, rf_accuracy = random_forest_evaluation(
        X_train, X_test, y_train, y_test
    )
    _, gnb_report, gnb_accuracy = gaussian_nb_evaluation(
        X_train, X_test, y_train, y_test
    )
    _, lsvc_report, lsvc_accuracy = linear_svc_evaluation(
        X_train, X_test, y_train, y_test
    )
    _, ada_report, ada_accuracy = adaboost_evaluation(X_train, X_test, y_

    print("\nLogistic Regression")
    print(lr_report)
    print("Accuracy Score:", lr_accuracy)
    print("-----------------------------------------------------------")

    print("\nRandom Forest")
    print(rf_report)
    print("Accuracy Score:", rf_accuracy)
    print("-----------------------------------------------------------")

    print("\nNaive Bayes")
    print(gnb_report)
    print("Accuracy Score:", gnb_accuracy)
    print("-----------------------------------------------------------")

    print("\nLinear SVC")
    print(lsvc_report)
    print("Accuracy Score:", lsvc_accuracy)
    print("-----------------------------------------------------------")
```

```python
    print("\nAdaBoost")
    print(ada_report)
    print("Accuracy Score:", ada_accuracy)
    print("-----------------------------------------------------------")

    accuracies = [lr_accuracy, rf_accuracy, gnb_accuracy, lsvc_accuracy,

    return accuracies


# Plot the evaluation report for the models
def plot_evaluation_report(accuracies, title="Model Accuracies"):
    models = [
        "Logistic Regression",
        "Random Forest",
        "Gaussian NB",
        "Linear SVC",
        "AdaBoost",
    ]

    plt.figure(figsize=(10, 5))
    plt.bar(models, accuracies)
    plt.ylabel("Accuracy")
    plt.title(title)
    plt.show()
```

In [11]:
```python
text_vectorizer = TfidfVectorizer(
    ngram_range=(1, 2), max_df=0.75, min_df=5, max_features=10000
)

# TF-IDF feature matrix
text_features = text_vectorizer.fit_transform(dataset["processed_tweets"]
tfidf_array = text_features.toarray()
```

Using TFIDF to train multiple models without extra features

In [12]:
```python
X = text_features
y = dataset["class"].astype(int)

X_train_tfidf, X_test_tfidf, y_train, y_test = train_test_split(
    X, y, random_state=42, test_size=0.2
)
```

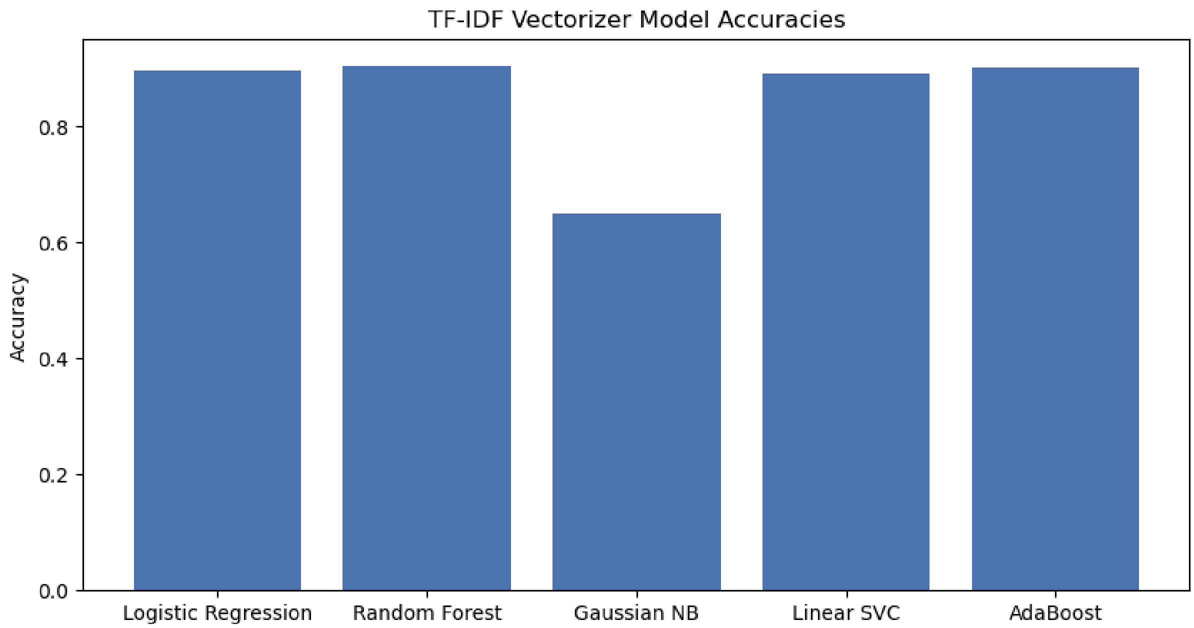
In [13]:
```
tfidf_accuracies = evaluate_models(X_train_tfidf, X_test_tfidf, y_train,
```

```
Logistic Regression
              precision    recall  f1-score   support

           0       0.56      0.18      0.27       290
           1       0.92      0.96      0.94      3832
           2       0.85      0.84      0.85       835

    accuracy                           0.90      4957
   macro avg       0.77      0.66      0.68      4957
weighted avg       0.88      0.90      0.88      4957

Accuracy Score: 0.8977203954004438
----------------------------------------------------------

Random Forest
              precision    recall  f1-score   support

           0       0.54      0.18      0.27       290
           1       0.93      0.96      0.94      3832
           2       0.83      0.92      0.87       835

    accuracy                           0.91      4957
   macro avg       0.77      0.69      0.70      4957
weighted avg       0.89      0.91      0.89      4957

Accuracy Score: 0.905184587452088
----------------------------------------------------------

Naive Bayes
              precision    recall  f1-score   support

           0       0.10      0.39      0.16       290
           1       0.89      0.68      0.77      3832
           2       0.54      0.58      0.56       835

    accuracy                           0.65      4957
   macro avg       0.51      0.55      0.50      4957
weighted avg       0.79      0.65      0.70      4957

Accuracy Score: 0.6491829735727255
----------------------------------------------------------

Linear SVC
              precision    recall  f1-score   support

           0       0.46      0.26      0.33       290
           1       0.92      0.95      0.94      3832
           2       0.83      0.85      0.84       835

    accuracy                           0.89      4957
   macro avg       0.74      0.69      0.70      4957
weighted avg       0.88      0.89      0.89      4957

Accuracy Score: 0.8926770223925762
----------------------------------------------------------
```

```
AdaBoost
              precision    recall  f1-score   support

           0       0.42      0.16      0.23       290
           1       0.94      0.95      0.94      3832
           2       0.80      0.94      0.87       835

    accuracy                           0.90      4957
   macro avg       0.72      0.68      0.68      4957
weighted avg       0.89      0.90      0.89      4957

Accuracy Score: 0.9005446842848497
----------------------------------------------------------
```

In [14]:

```
plot_evaluation_report(tfidf_accuracies, "TF-IDF Vectorizer Model Accura
```



Using polarity scores as features from Sentiment Analysis

In [15]:
```
# Download the VADER lexicon for sentiment analysis
nltk.download("vader_lexicon")

# Initialize the sentiment intensity analyzer
sentiment_analyzer = SentimentIntensityAnalyzer()


def count_tags(text):
    # Patterns for matching spaces, URLs, mentions, and hashtags
    space_pattern = r"\s+"
    url_pattern = r"http[s]?://\S+"
    mention_pattern = r"@[\w\-]+"
    hashtag_pattern = r"#[\w\-]+"

    # Replace matches with placeholders
    text = re.sub(space_pattern, " ", text)
    text = re.sub(url_pattern, "URLHERE", text)
    text = re.sub(mention_pattern, "MENTIONHERE", text)
    text = re.sub(hashtag_pattern, "HASHTAGHERE", text)

    # Count occurrences of each placeholder
    return (
        text.count("URLHERE"),
        text.count("MENTIONHERE"),
        text.count("HASHTAGHERE"),
    )


def sentiment_analysis(tweet):
    sentiment = sentiment_analyzer.polarity_scores(tweet)
    twitter_objs = count_tags(tweet)
    features = [
        sentiment["neg"],
        sentiment["pos"],
        sentiment["neu"],
        sentiment["compound"],
        *twitter_objs,  # Unpack the tag counts directly into the list
    ]
    return features


def sentiment_analysis_features(tweets):
    return np.array([sentiment_analysis(tweet) for tweet in tweets])


sentiment_features = sentiment_analysis_features(tweet)

# Create a DataFrame from the numpy array of features
new_features = pd.DataFrame(
    sentiment_features,
    columns=["Neg", "Pos", "Neu", "Compound", "url_tag", "mention_tag", '
)

new_features
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     /Users/Keerthi/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

Out[15]:

	Neg	Pos	Neu	Compound	url_tag	mention_tag	hash_tag
0	0.000	0.120	0.880	0.4563	0.0	1.0	0.0
1	0.237	0.000	0.763	-0.6876	0.0	1.0	0.0
2	0.538	0.000	0.462	-0.9550	0.0	2.0	0.0
3	0.000	0.344	0.656	0.5673	0.0	2.0	0.0
4	0.249	0.081	0.669	-0.7762	0.0	1.0	1.0
...	...	...	...	...	...	...	...
24778	0.000	0.000	1.000	0.0000	0.0	3.0	3.0
24779	0.454	0.000	0.546	-0.8074	0.0	0.0	0.0
24780	0.000	0.219	0.781	0.4738	0.0	0.0	0.0
24781	0.573	0.000	0.427	-0.7717	0.0	0.0	0.0
24782	0.000	0.218	0.782	0.5994	1.0	0.0	0.0

24783 rows × 7 columns

Using TFIDF and sentiment features to train multiple models

In [16]:

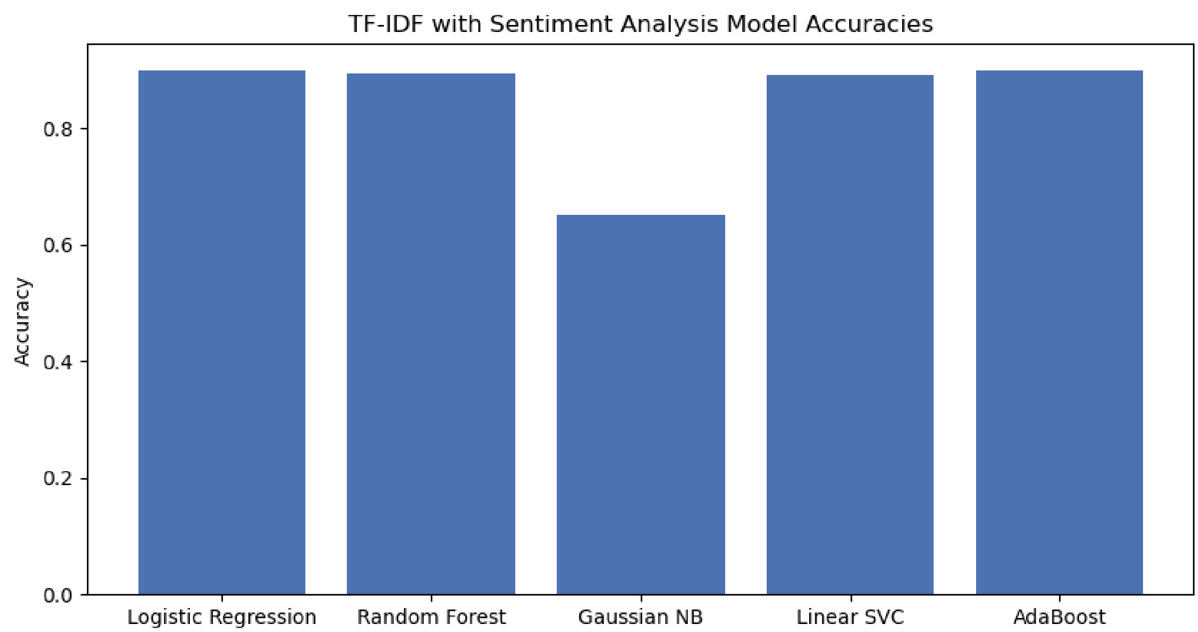
```
tfidf_sentiment_features = np.concatenate([tfidf_array, sentiment_featur

X = pd.DataFrame(tfidf_sentiment_features)

X_train_sa, X_test_sa, y_train, y_test = train_test_split(
    X, y, random_state=42, test_size=0.2
)
```

In [17]:
```
sa_accuracies = evaluate_models(X_train_sa, X_test_sa, y_train, y_test)
```

```
Logistic Regression
              precision    recall  f1-score   support

           0       0.59      0.18      0.28       290
           1       0.92      0.96      0.94      3832
           2       0.85      0.84      0.84       835

    accuracy                           0.90      4957
   macro avg       0.78      0.66      0.69      4957
weighted avg       0.89      0.90      0.88      4957

Accuracy Score: 0.898325600161388
----------------------------------------------------------

Random Forest
              precision    recall  f1-score   support

           0       0.51      0.14      0.22       290
           1       0.91      0.96      0.94      3832
           2       0.84      0.84      0.84       835

    accuracy                           0.89      4957
   macro avg       0.75      0.65      0.66      4957
weighted avg       0.88      0.89      0.88      4957

Accuracy Score: 0.8936856969941497
----------------------------------------------------------

Naive Bayes
              precision    recall  f1-score   support

           0       0.10      0.39      0.16       290
           1       0.89      0.68      0.77      3832
           2       0.54      0.59      0.56       835

    accuracy                           0.65      4957
   macro avg       0.51      0.55      0.50      4957
weighted avg       0.79      0.65      0.70      4957

Accuracy Score: 0.650191648174299
----------------------------------------------------------

Linear SVC
              precision    recall  f1-score   support

           0       0.45      0.26      0.33       290
           1       0.92      0.95      0.94      3832
           2       0.83      0.85      0.84       835

    accuracy                           0.89      4957
   macro avg       0.73      0.69      0.70      4957
weighted avg       0.88      0.89      0.88      4957

Accuracy Score: 0.8916683477910026
----------------------------------------------------------
```

```
AdaBoost
              precision    recall  f1-score   support

           0       0.44      0.14      0.21       290
           1       0.93      0.95      0.94      3832
           2       0.81      0.92      0.86       835

    accuracy                           0.90      4957
   macro avg       0.73      0.67      0.67      4957
weighted avg       0.88      0.90      0.89      4957

Accuracy Score: 0.9001412144442204
----------------------------------------------------------
```

In [18]:
```
plot_evaluation_report(sa_accuracies, "TF-IDF with Sentiment Analysis Mo
```



Doc2Vec Vector Columns

In [19]:
```
# Prepare the data for Doc2Vec model
# Each tweet is tokenized and tagged with its index in the dataset
tagged_documents = [
    TaggedDocument(words=tweet.split(" "), tags=[index])
    for index, tweet in enumerate(dataset["processed_tweets"])
]

doc2vec_model = Doc2Vec(
    documents=tagged_documents, vector_size=5, window=2, min_count=1, wo
)


# Transform tweets into their vector representation using the trained Do
def tweet_to_vector(tweet):
    return doc2vec_model.infer_vector(tweet.split(" "))


# Transform each tweet in the 'processed_tweets' column to a vector, and
doc_vectors = dataset["processed_tweets"].apply(tweet_to_vector).apply(p

# Rename columns to 'doc2vec_vector_X' where X is the column index
doc_vectors.columns = ["doc2vec_vector_" + str(i) for i in doc_vectors.c

doc_vectors
```

Out[19]:

	doc2vec_vector_0	doc2vec_vector_1	doc2vec_vector_2	doc2vec_vector_3	doc2vec_vector_
0	0.087699	-0.012394	-0.136874	-0.107608	0.10218
1	0.154739	0.083603	0.120069	0.126898	-0.04211
2	-0.019824	0.023394	0.058932	-0.113951	-0.01952
3	0.068563	0.050330	0.066745	-0.024027	0.07325
4	0.046394	-0.007000	0.124255	-0.158435	-0.08697
...	...	...	...	...	.
24778	0.142136	0.019422	0.288841	-0.183006	0.17402
24779	0.097965	0.149767	-0.098101	-0.168777	-0.10662
24780	-0.089103	0.219651	-0.053201	-0.009310	-0.27927
24781	0.095359	0.099429	0.092663	-0.114187	-0.14921
24782	0.281260	-0.010077	0.744882	-0.221786	0.10107

24783 rows × 5 columns

Using TFIDF with sentiment features and doc2vec to train multiple models

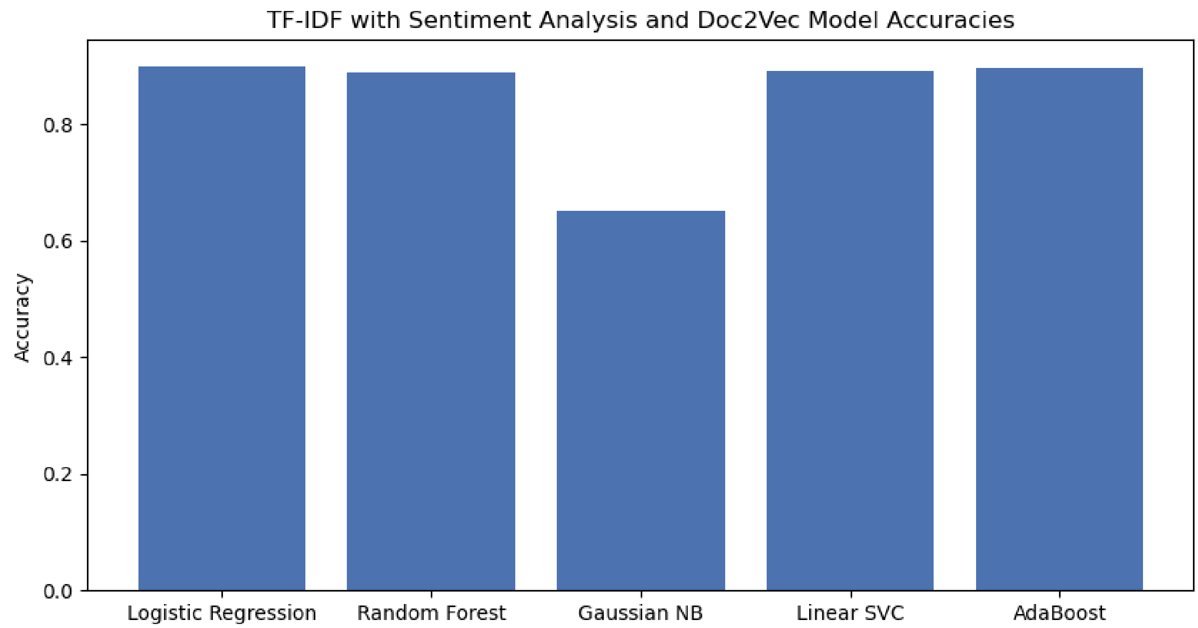
In [20]:
```
tfidf_sa_d2v_features = np.concatenate(
    [tfidf_array, sentiment_features, doc_vectors], axis=1
)

X = pd.DataFrame(tfidf_sa_d2v_features)

X_train_d2v, X_test_d2v, y_train, y_test = train_test_split(
    X, y, random_state=42, test_size=0.2
)
```

In [21]:
```
d2v_accuracies = evaluate_models(X_train_d2v, X_test_d2v, y_train, y_tes
```

```
Logistic Regression
              precision    recall  f1-score   support

           0       0.60      0.18      0.28       290
           1       0.92      0.97      0.94      3832
           2       0.85      0.85      0.85       835

    accuracy                           0.90      4957
   macro avg       0.79      0.67      0.69      4957
weighted avg       0.89      0.90      0.89      4957

Accuracy Score: 0.9001412144442204
-----------------------------------------------------------

Random Forest
              precision    recall  f1-score   support

           0       0.50      0.07      0.12       290
           1       0.90      0.97      0.94      3832
           2       0.86      0.79      0.82       835

    accuracy                           0.89      4957
   macro avg       0.75      0.61      0.63      4957
weighted avg       0.87      0.89      0.87      4957

Accuracy Score: 0.8898527335081703
-----------------------------------------------------------

Naive Bayes
              precision    recall  f1-score   support

           0       0.10      0.39      0.16       290
           1       0.89      0.68      0.77      3832
           2       0.54      0.59      0.56       835

    accuracy                           0.65      4957
   macro avg       0.51      0.55      0.50      4957
weighted avg       0.79      0.65      0.70      4957

Accuracy Score: 0.650191648174299
-----------------------------------------------------------

Linear SVC
              precision    recall  f1-score   support

           0       0.45      0.26      0.33       290
           1       0.92      0.95      0.94      3832
           2       0.83      0.85      0.84       835

    accuracy                           0.89      4957
   macro avg       0.74      0.69      0.70      4957
weighted avg       0.88      0.89      0.89      4957

Accuracy Score: 0.8926770223925762
-----------------------------------------------------------
```

```
AdaBoost
              precision    recall  f1-score   support

           0       0.40      0.18      0.25       290
           1       0.93      0.95      0.94      3832
           2       0.82      0.91      0.86       835

    accuracy                           0.90      4957
   macro avg       0.72      0.68      0.68      4957
weighted avg       0.88      0.90      0.89      4957

Accuracy Score: 0.8967117207988703
----------------------------------------------------------
```

In [22]:
```
plot_evaluation_report(
    d2v_accuracies, "TF-IDF with Sentiment Analysis and Doc2Vec Model Acc
)
```



In [23]:
```
# Calculate readability features for a given tweet
def calculate_readability_features(tweet):
    # Count the number of syllables in the text
    syllable_count = textstat.syllable_count(tweet)
    # Count the total number of characters excluding spaces
    character_count_excluding_spaces = sum(len(word) for word in tweet)
    # Count the total number of characters including spaces
    character_count_including_spaces = len(tweet)
    # Count the number of words
    word_count = len(tweet.split())
    # Calculate the average number of syllables per word
    average_syllables_per_word = round(
        (syllable_count + 0.001) / (word_count + 0.001), 4
    )
    # Count the number of unique words
    unique_word_count = len(set(tweet.split()))

    # Calculate the Flesch-Kincaid Readability Score
    flesch_kincaid_readability = round(
        0.39 * word_count + 11.8 * average_syllables_per_word - 15.59, 1
    )
    # Calculate the Flesch Reading Ease Score
    flesch_reading_ease = round(
        206.835 - 1.015 * word_count - 84.6 * average_syllables_per_word
    )

    readability_features = [
        flesch_kincaid_readability,
        flesch_reading_ease,
        syllable_count,
        average_syllables_per_word,
        character_count_excluding_spaces,
        character_count_including_spaces,
        word_count,
        unique_word_count,
    ]

    return readability_features


# Extract enhanced readability features from a collection of tweets
def extract_enhanced_features_from_tweets(tweets):
    return np.array([calculate_readability_features(tweet) for tweet in t


enhanced_features = extract_enhanced_features_from_tweets(processed_twee
enhanced_features
```

Out[23]:
```
array([[  3.7 ,  84.9 ,  12.  , ...,  50.  ,   9.  ,   9.  ],
       [  2.6 ,  95.69,  13.  , ...,  49.  ,  11.  ,  10.  ],
       [  2.3 ,  92.97,  10.  , ...,  42.  ,   8.  ,   8.  ],
       ...,
       [  2.5 ,  95.17,  12.  , ...,  51.  ,  10.  ,  10.  ],
       [ -1.4 , 116.15,   6.  , ...,  30.  ,   6.  ,   6.  ],
       [  5.8 ,  76.5 ,  18.  , ...,  77.  ,  13.  ,  13.  ]])
```

Using TFIDF with sentiment features,doc2vec and enhanced features to train multiple modles

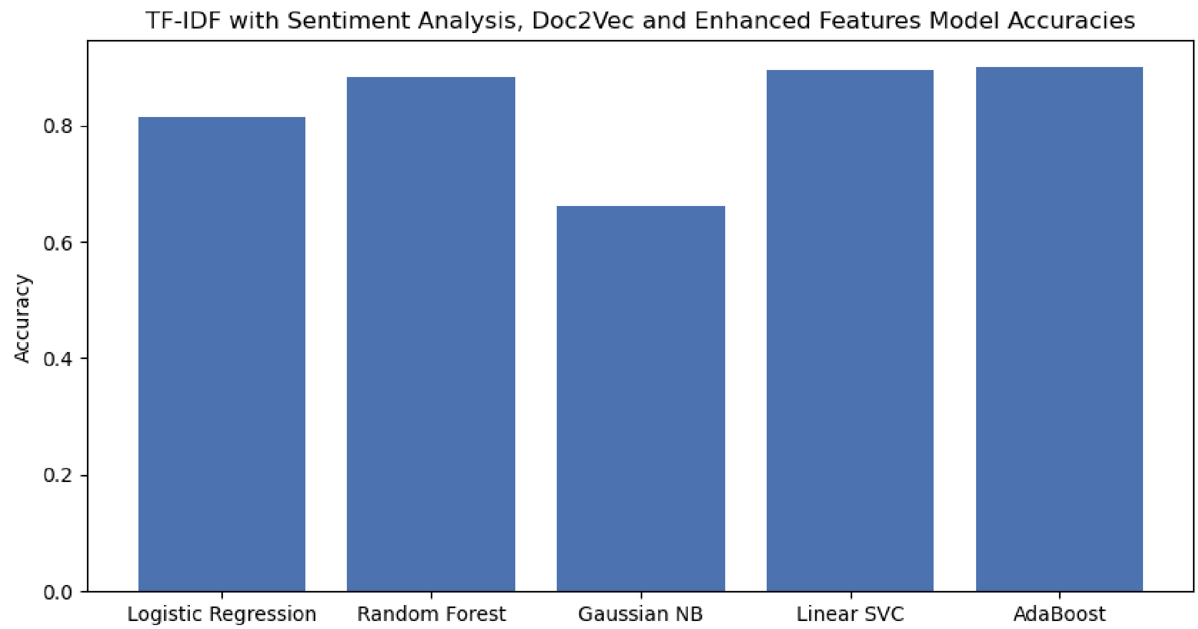
In [24]:
```
tfidf_sa_d2v_enh_features = np.concatenate(
    [tfidf_array, sentiment_features, doc_vectors, enhanced_features], a
)

X = pd.DataFrame(tfidf_sa_d2v_enh_features)

X_train_enh, X_test_enh, y_train, y_test = train_test_split(
    X, y, random_state=0, test_size=0.2
)
```

In [25]:
```
enh_accuracies = evaluate_models(X_train_enh, X_test_enh, y_train, y_tes
```

```
Logistic Regression
              precision    recall  f1-score   support

           0       1.00      0.00      0.01       279
           1       0.84      0.95      0.89      3852
           2       0.64      0.43      0.52       826

    accuracy                           0.81      4957
   macro avg       0.83      0.46      0.47      4957
weighted avg       0.81      0.81      0.78      4957

Accuracy Score: 0.8133951987088965
----------------------------------------------------------

Random Forest
              precision    recall  f1-score   support

           0       0.50      0.06      0.10       279
           1       0.89      0.97      0.93      3852
           2       0.85      0.73      0.78       826

    accuracy                           0.88      4957
   macro avg       0.75      0.59      0.61      4957
weighted avg       0.86      0.88      0.86      4957

Accuracy Score: 0.881783336695582
----------------------------------------------------------

Naive Bayes
              precision    recall  f1-score   support

           0       0.09      0.36      0.15       279
           1       0.90      0.69      0.78      3852
           2       0.59      0.65      0.62       826

    accuracy                           0.66      4957
   macro avg       0.53      0.57      0.51      4957
weighted avg       0.80      0.66      0.72      4957

Accuracy Score: 0.662497478313496
----------------------------------------------------------

Linear SVC
              precision    recall  f1-score   support

           0       0.60      0.10      0.17       279
           1       0.91      0.97      0.94      3852
           2       0.83      0.83      0.83       826

    accuracy                           0.89      4957
   macro avg       0.78      0.63      0.65      4957
weighted avg       0.88      0.89      0.88      4957

Accuracy Score: 0.8948961065160379
----------------------------------------------------------
```

```
AdaBoost
              precision    recall  f1-score   support

           0       0.48      0.22      0.30       279
           1       0.93      0.95      0.94      3852
           2       0.82      0.90      0.86       826

    accuracy                           0.90      4957
   macro avg       0.74      0.69      0.70      4957
weighted avg       0.89      0.90      0.89      4957

Accuracy Score: 0.9005446842848497
----------------------------------------------------------
```

In [26]:
```
plot_evaluation_report(
    enh_accuracies,
    "TF-IDF with Sentiment Analysis, Doc2Vec and Enhanced Features Model
)
```



Using TFIDF with sentiment fearures,doc2vec,enhanced features and word2vec to train multiple models

In [27]:
```
# Prepare the data for Word2Vec model
sentences = dataset["processed_tweets"].apply(lambda x: x.split(" ")).to


word2vec_model = Word2Vec(sentences, vector_size=5, window=2, min_count=


# Convert tweets to a vector
def document_vector(model, doc):
    # remove out-of-vocabulary words
    doc = [word for word in doc if word in model.wv.index_to_key]
    if not doc:
        return np.zeros(model.vector_size)
    return np.mean(model.wv[doc], axis=0)


# Apply the function to each document to get a vector
word_vectors = dataset["processed_tweets"].apply(
    lambda x: document_vector(word2vec_model, x.split(" "))
)
word_vectors = pd.DataFrame(word_vectors.tolist())
word_vectors.columns = [
    "word2vec_vector_" + str(i) for i in range(word_vectors.shape[1])
]

word_vectors
```

Out[27]:

	word2vec_vector_0	word2vec_vector_1	word2vec_vector_2	word2vec_vector_3	word2vec_v
0	0.477393	1.047343	3.002040	-1.695943	-0.
1	0.228817	1.008271	2.185996	-1.330619	-0.
2	0.041948	1.279049	2.856897	-1.665177	-0.
3	0.907234	1.945787	2.758926	-1.820140	-0.
4	0.157035	1.098243	2.626052	-1.403496	-0.
...	...	...	...	...	
24778	0.174940	0.600728	1.499320	-0.843360	-0.
24779	0.243958	0.902655	2.421834	-1.358724	-0.
24780	0.478748	1.514069	2.679154	-1.652333	-0.
24781	-0.093642	1.025461	2.050463	-1.031344	-0.
24782	0.456050	0.407682	1.508928	-0.809081	-0.

24783 rows × 5 columns

In [28]:
```
tfidf_sa_d2v_enh_w2v_features = np.concatenate(
    [tfidf_array, sentiment_features, doc_vectors, enhanced_features, wo
    axis=1,
)

X = pd.DataFrame(tfidf_sa_d2v_enh_w2v_features)

X_train_w2v, X_test_w2v, y_train, y_test = train_test_split(
    X, y, random_state=0, test_size=0.2
)
```

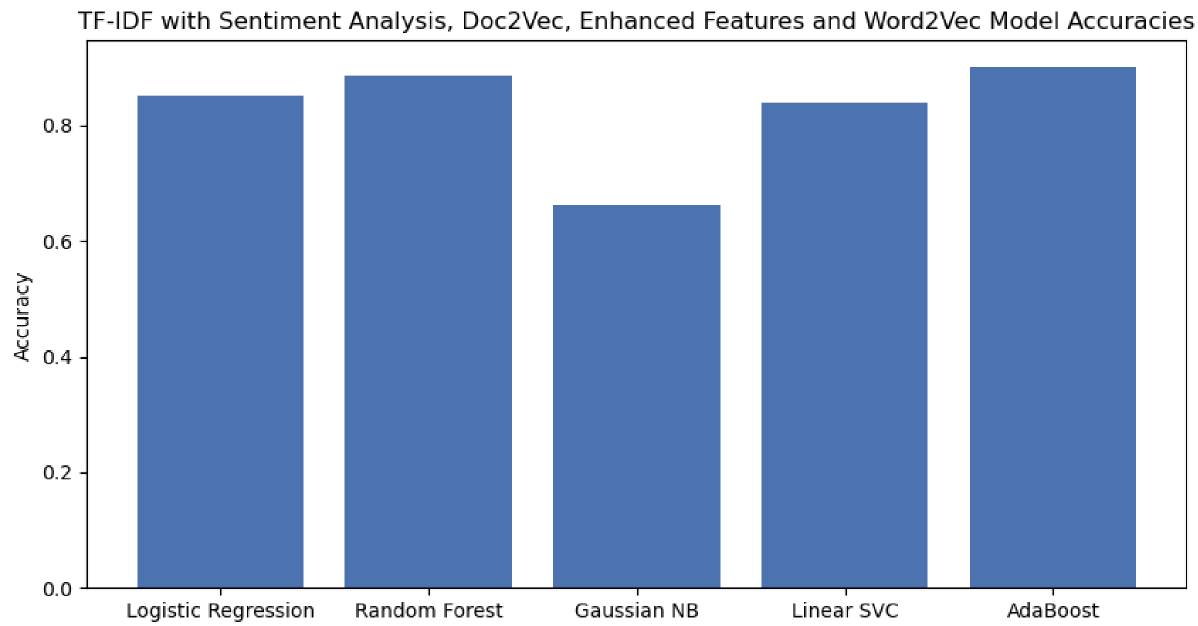
In [29]:
```
w2v_accuracies = evaluate_models(X_train_w2v, X_test_w2v, y_train, y_tes
```

```
Logistic Regression
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       279
           1       0.88      0.96      0.91      3852
           2       0.72      0.65      0.68       826

    accuracy                           0.85      4957
   macro avg       0.53      0.54      0.53      4957
weighted avg       0.80      0.85      0.82      4957

Accuracy Score: 0.8519265684890055
-----------------------------------------------------------

Random Forest
              precision    recall  f1-score   support

           0       0.52      0.04      0.08       279
           1       0.90      0.97      0.93      3852
           2       0.82      0.78      0.80       826

    accuracy                           0.89      4957
   macro avg       0.75      0.60      0.60      4957
weighted avg       0.87      0.89      0.86      4957

Accuracy Score: 0.8862215049425055
-----------------------------------------------------------

Naive Bayes
              precision    recall  f1-score   support

           0       0.09      0.36      0.15       279
           1       0.90      0.69      0.78      3852
           2       0.59      0.65      0.62       826

    accuracy                           0.66      4957
   macro avg       0.53      0.57      0.51      4957
weighted avg       0.80      0.66      0.72      4957

Accuracy Score: 0.662497478313496
-----------------------------------------------------------

Linear SVC
              precision    recall  f1-score   support

           0       0.52      0.14      0.22       279
           1       0.84      0.98      0.91      3852
           2       0.87      0.42      0.56       826

    accuracy                           0.84      4957
   macro avg       0.74      0.51      0.56      4957
weighted avg       0.83      0.84      0.81      4957

Accuracy Score: 0.8386120637482348
-----------------------------------------------------------
```

```
AdaBoost
              precision    recall  f1-score   support

           0       0.54      0.22      0.31       279
           1       0.93      0.95      0.94      3852
           2       0.82      0.90      0.86       826

    accuracy                           0.90      4957
   macro avg       0.76      0.69      0.70      4957
weighted avg       0.89      0.90      0.89      4957

Accuracy Score: 0.9013516239661086
----------------------------------------------------------
```

In [30]:

```
plot_evaluation_report(
    w2v_accuracies,
    "TF-IDF with Sentiment Analysis, Doc2Vec, Enhanced Features and Word2
)
```



In [36]:
```
# table of accuracies in percentage
accuracies = {
    "TF-IDF": [round(acc * 100, 2) for acc in tfidf_accuracies],
    "TF-IDF + Sentiment Analysis": [round(acc * 100, 2) for acc in sa_ac
    "TF-IDF + Sentiment Analysis + Doc2Vec": [
        round(acc * 100, 2) for acc in d2v_accuracies
    ],
    "TF-IDF + Sentiment Analysis + Doc2Vec + Enhanced Features": [
        round(acc * 100, 2) for acc in enh_accuracies
    ],
    "TF-IDF + Sentiment Analysis + Doc2Vec + Enhanced Features + Word2Ve
        round(acc * 100, 2) for acc in w2v_accuracies
    ],
}

accuracies_df = pd.DataFrame(accuracies)
accuracies_df.index = [
    "Logistic Regression",
    "Random Forest",
    "Naive Bayes",
    "Linear SVC",
    "AdaBoost",
]
accuracies_df.transpose()
```

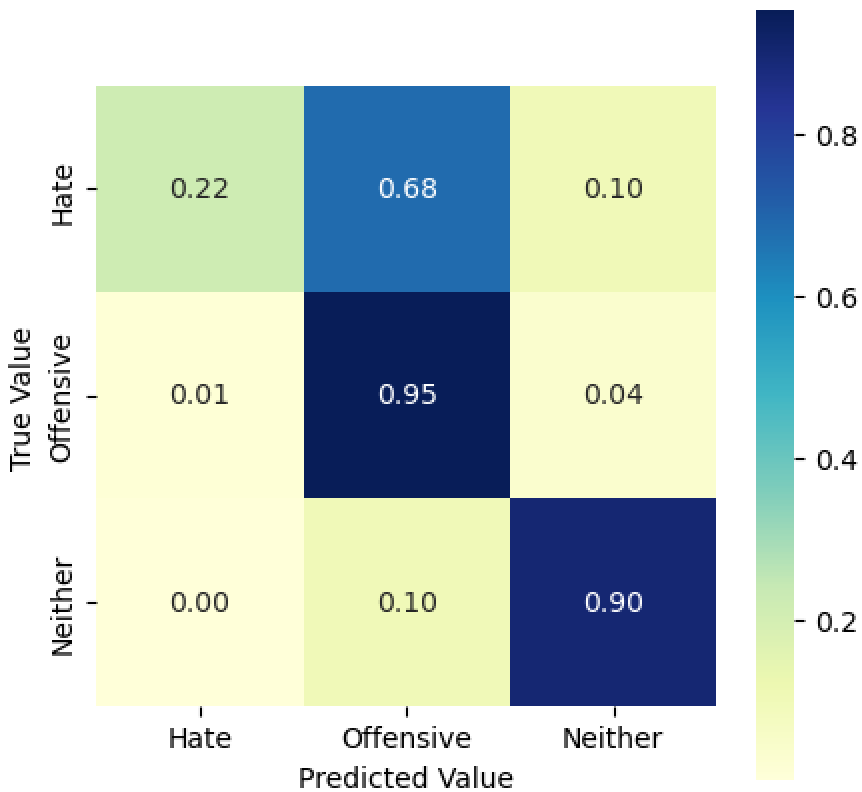
Out[36]:

	Logistic Regression	Random Forest	Naive Bayes	Linear SVC	AdaBoost
TF-IDF	89.77	90.52	64.92	89.27	90.05
TF-IDF + Sentiment Analysis	89.83	89.37	65.02	89.17	90.01
TF-IDF + Sentiment Analysis + Doc2Vec	90.01	88.99	65.02	89.27	89.67
TF-IDF + Sentiment Analysis + Doc2Vec + Enhanced Features	81.34	88.18	66.25	89.49	90.05
TF-IDF + Sentiment Analysis + Doc2Vec + Enhanced Features + Word2Vec	85.19	88.62	66.25	83.86	90.14

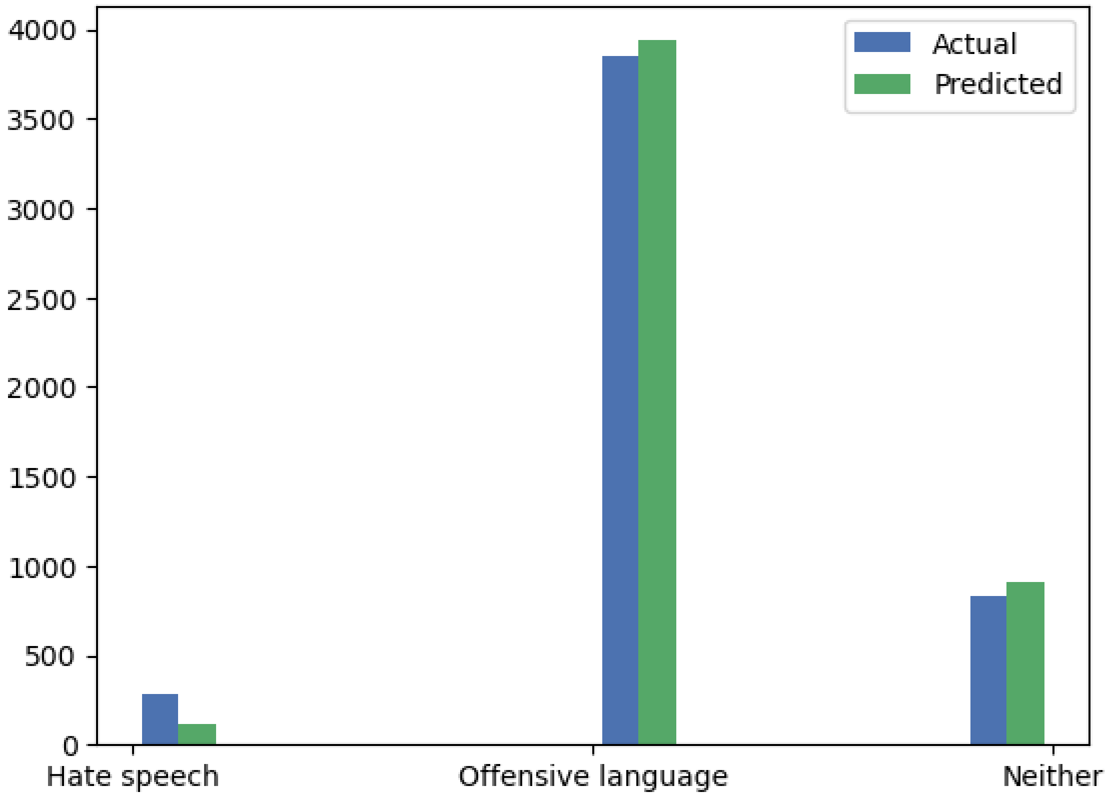
In [32]:
```
y_preds, _, _ = adaboost_evaluation(X_train_w2v, X_test_w2v, y_train, y_
```

In [33]:
```
matrix = confusion_matrix(y_test, y_preds)

matrix_proportions = np.zeros((3, 3))
for i in range(0, 3):
    matrix_proportions[i, :] = matrix[i, :] / float(matrix[i, :].sum())

names = ["Hate", "Offensive", "Neither"]
confusion_df = pd.DataFrame(matrix_proportions, index=names, columns=nam

plt.figure(figsize=(5, 5))
sns.heatmap(
    confusion_df,
    annot=True,
    cmap="YlGnBu",
    square=True,
    fmt=".2f",
)
plt.ylabel("True Value")
plt.xlabel("Predicted Value")
plt.show()
```

Out[33]:
```
Text(0.5, 63.222222222222186, 'Predicted Value')
```



In [34]:
```
ax = plt.axes()
ax.set_xticks([0, 1, 2])
ax.set_xticklabels(["Hate speech", "Offensive language", "Neither"])

plt.hist([y_test, pd.Series(y_preds)], label=["Actual", "Predicted"])

plt.legend()
plt.show()
```



In [ ]: