finans sektöründe atılan tweetlerden duygu analizi yapılmaya çalışıldı.

1.Kütüphanelerin yüklenmesi

- BOW
  - NB
  - SVM
  - LOGISTIC REG
  - Decission Tree
  - Random Forest

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import nltk
from nltk.stem.porter import *
nltk.download('gutenberg')
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('averaged_perceptron_tagger')

from nltk.tokenize import TweetTokenizer
from nltk.tokenize import word_tokenize, sent_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()
import datetime

from scipy import stats
from scipy.sparse import hstack, csr_matrix
from sklearn.model_selection import train_test_split, cross_val_score

from collections import Counter
from nltk.corpus import stopwords
from nltk.util import ngrams

import string
import gensim
from gensim.models.phrases import Phraser, Phrases
from gensim.models.word2vec import Word2Vec
from sklearn.manifold import TSNE

from sklearn.feature_extraction.text import TfidfVectorizer
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.multiclass import OneVsRestClassifier
pd.set_option('max_colwidth',400)
from bs4 import BeautifulSoup
import re

from tqdm import tqdm
from bokeh.io import output_notebook, output_file
from bokeh.plotting import show, figure
%matplotlib inline
from collections import defaultdict
```

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

```
from nltk import pos_tag
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from sklearn.preprocessing import LabelEncoder
from collections import defaultdict
from nltk.corpus import wordnet as wn
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn import model_selection, naive_bayes, svm
from sklearn.metrics import accuracy_score
import warnings
warnings.filterwarnings("ignore")

from keras.utils import to_categorical
import random
from sklearn.model_selection import train_test_split
from keras.preprocessing import sequence

"""Aşağıdaki kodun Eskisi from keras.preprocessing.text import
Tokenizer"""
from tensorflow.keras.preprocessing.text import Tokenizer

from keras.layers import Dense,Dropout,Embedding,LSTM
from keras.callbacks import EarlyStopping
from keras.losses import categorical_crossentropy
```

```
from keras.optimizers import Adam
from keras.models import Sequential

warnings.filterwarnings('ignore')
from google.colab import drive
drive.mount('/content/drive')
%cd /content/drive/My Drive/fintek/
df=pd.read_csv("cleaned_df.csv",index_col=0)
```

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
/content/drive/My Drive/fintek
```

```
df = pd.read_csv('cleaned_df.csv', header=0)
print(df.head(20))
```

```
    Unnamed: 0
text  \
0            0           spicejet to issue 4 crore warrants to
promoters
1            1                             mmtc q2 net loss at rs 4
crore
2            2         mid cap funds can deliver more  stay put
experts
3            3                     mid caps now turn into market
darlings
4            4  market seeing patience  if not conviction  prakash
diwan
5            5           infosys  will the strong volume growth
sustain
6            6                      hudco raises rs cr via tax free
bonds
7            7               hoec could retest 35 levels  ashwani
gujral
8            8              genpact appoints edward j fitzpatrick as
cfo
9            9            exl beats profit estimates  cuts sales
outlook
10          10            wait and watch on bharti airtel  vinay
khattar
11          11       would stick to banking  girish pai  centrum
broking
12          12                msci adds aurobindo pharma to india
index
13          13                ashok leyland raises rs crore through
qip
14          14                           at wipro  growth remains a
mirage
15          15          why chinese stocks leave us investors
vulnerable
```

```
16          16              us stocks finish mixed amid more tech
selling
17          17                 opec reduces estimate on oil demand
growth
18          18                 oil prices mixed ahead of us supply
report
19          19                       makemytrip expands share sale
plan

    score
0     0.0
1     0.0
2     1.0
3     1.0
4     0.0
5     0.0
6     1.0
7     0.0
8     0.0
9     1.0
10    0.0
11    1.0
12    1.0
13    1.0
14   -1.0
15   -1.0
16   -1.0
17   -1.0
18    0.0
19    0.0
```

```
df.isnull().values.any()
```

```
df.head()
```


```
{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 21862,\n  \"fields\":
[\n    {\n      \"column\": \"Unnamed: 0\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 6311,\n        \"min\": 0,\n
\"max\": 21861,\n        \"num_unique_values\": 21862,\n
\"samples\": [\n          7886,\n          12956,\n          20484\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"text\",\n      \"properties\":
{\n        \"dtype\": \"string\",\n        \"num_unique_values\":
15999,\n        \"samples\": [\n          \"underweight on commodities
vijai mantri  pramerica mf\",\n          \"brokerage firms like anand
rathi securities  motilal oswal securities  angel broking looking at
alliances as market loses footing\",\n          \"bosch ltd posts q2
net profit of rs crore\"\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"score\",\n      \"properties\": {\n        \"dtype\":
```

```
\"number\",\n        \"std\": 0.7300226654189315,\n        \"min\": -
1.0,\n        \"max\": 1.0,\n        \"num_unique_values\": 3,\n
\"samples\": [\n          0.0,\n          1.0,\n          -1.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\n}","type":"dataframe","variable_name":"df"}
```

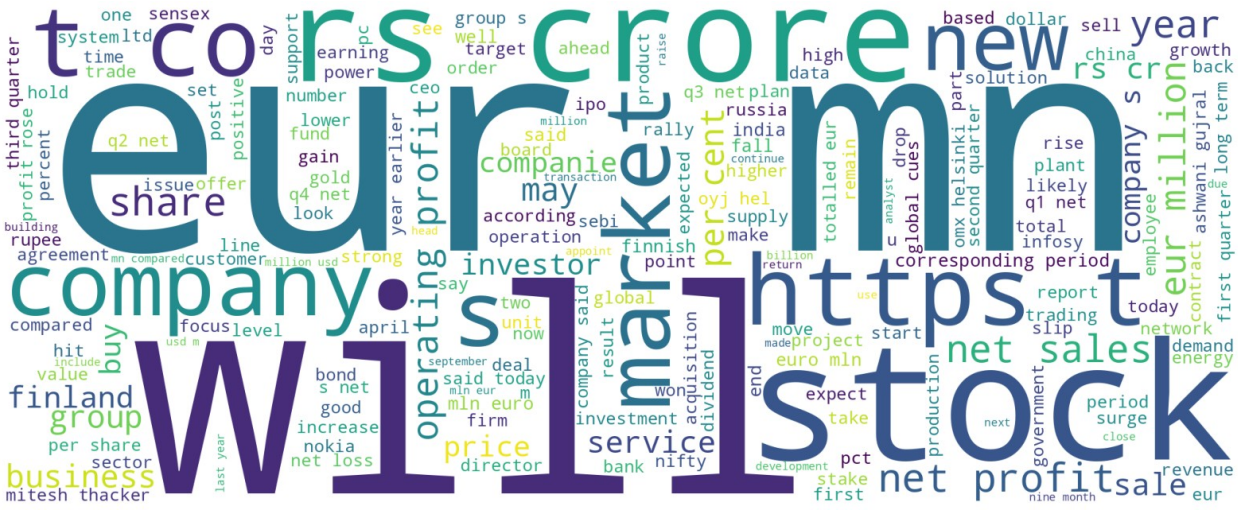
```
print(len(df))
```

```
21862
```

```
   print(df.columns)
```

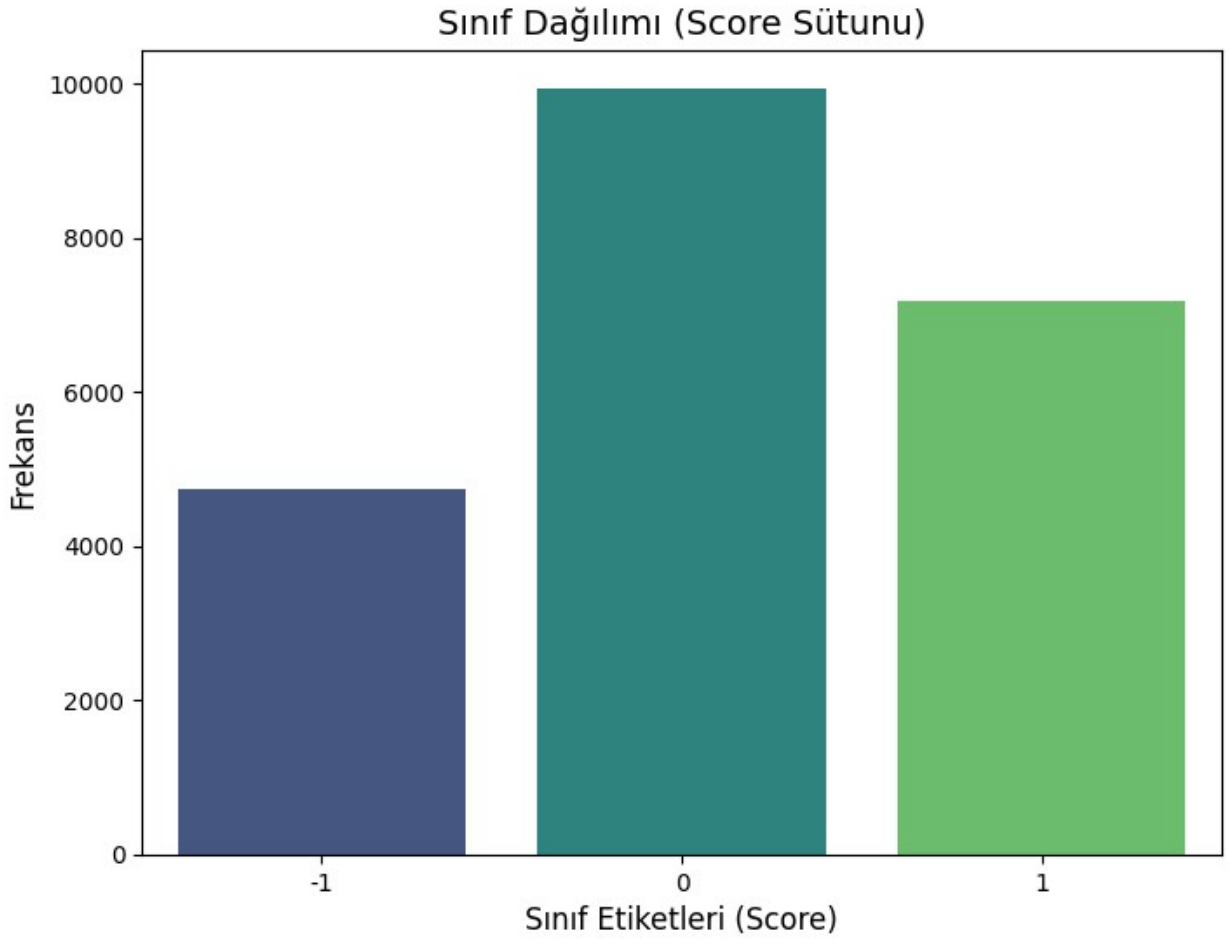
```
Index(['Unnamed: 0', 'text', 'score'], dtype='object')
```

```
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator

words  = " ".join(x for x in df.text)
plt.figure(figsize=(20,10))
wordcloud = WordCloud(background_color="white", width = 2000, height =
800).generate(words)
plt.imshow(wordcloud)
plt.axis("off")
plt.show()
```




```
import matplotlib.pyplot as plt
import seaborn as sns

# Veri Setini Yükleme
df = pd.read_csv('cleaned_df.csv')

# Sınıf Dağılımı
plt.figure(figsize=(8, 6))
sns.countplot(x='score', data=df, palette='viridis')
plt.title('Sınıf Dağılımı (Score Sütunu)', fontsize=14)
```

```
plt.xlabel('Sınıf Etiketleri (Score)', fontsize=12)
plt.ylabel('Frekans', fontsize=12)
plt.xticks(ticks=[0, 1, 2], labels=['-1', '0', '1'])
plt.show()
```




```
##DATA PREPROCESSING

import nltk
import pandas as pd
import re
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

# Download the required NLTK data packages
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('punkt_tab') # Download the punkt_tab data package
```

```
# Veri yükleme (örnek veri çerçevesi)
df = pd.read_csv("cleaned_df.csv")

# İlk 30 satırın ön işleme öncesi hali
print("Ön İşleme Öncesi İlk 30 Satır:\n")
print(df.head(30))

# 1. HTML Etiketlerini Çıkarma (Regex Yöntemi)
TAG_RE = re.compile(r'<[^>]+>')

def remove_tags(text):
    return TAG_RE.sub('', text)

# 2. Metin Temizleme
def clean_text(text):
    text = remove_tags(text)  # HTML etiketlerini çıkarma
    text = text.lower()  # Küçük harfe dönüştürme
    text = re.sub(r'[^\w\s]', '', text)  # Noktalama işaretlerini
kaldırma
    text = re.sub(r'\d+', '', text)  # Sayıları çıkarma
    text = re.sub(r'\s+', ' ', text).strip()  # Gereksiz boşlukları
temizleme
    return text

df['text'] = df['text'].apply(clean_text)

# 3. Tokenization (Kelimeye Ayırma) - Özel karakterleri çıkarma
def tokenize_text(text):
    tokens = word_tokenize(text)  # Kelimelere ayırma
    tokens = [word for word in tokens if re.match(r'^[A-Za-z]+$',
word)]  # Sadece harfleri içeren kelimeler
    return tokens

df['text'] = df['text'].apply(tokenize_text)

# 4. Stopword Kaldırma (Stopwords listesini özelleştir)
stop_words = set(stopwords.words('english'))
# Finans verisi olduğundan, "financial" gibi terimler bazen stopword
sayılmamalı, özelleştirilmiş stopword listesi
stop_words.update(['will', 'the', 'for', 'from', 'when', 'what',
'how', 'about', 'that', 'this', 'can', 'in', 'on', 'with'])

def remove_stopwords(tokens):
    return [word for word in tokens if word not in stop_words]

df['text'] = df['text'].apply(remove_stopwords)

# 5. Lemmatization (Kelimeleri Anlamlı Hallerine Getirme)
lemmatizer = WordNetLemmatizer()
```

```python
def lemmatize_words(tokens):
    return [lemmatizer.lemmatize(word) for word in tokens]

df['text'] = df['text'].apply(lemmatize_words)

# 6. Metni Tekrar Birleştirme (Vektörleştirme İçin)
df['text'] = df['text'].apply(lambda x: ' '.join(x))

# İlk 30 satırın ön işleme sonrası hali
print("\nÖn İşleme Sonrası İlk 30 Satır:\n")
print(df.head(30))
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt_tab.zip.

Ön İşleme Öncesi İlk 30 Satır:

    Unnamed: 0
text  \
0            0           spicejet to issue 4 crore warrants to
promoters
1            1                              mmtc q2 net loss at rs 4
crore
2            2         mid cap funds can deliver more  stay put
experts
3            3                     mid caps now turn into market
darlings
4            4  market seeing patience  if not conviction  prakash
diwan
5            5           infosys  will the strong volume growth
sustain
6            6                      hudco raises rs cr via tax free
bonds
7            7                hoec could retest 35 levels  ashwani
gujral
8            8              genpact appoints edward j fitzpatrick as
cfo
9            9            exl beats profit estimates  cuts sales
outlook
10          10            wait and watch on bharti airtel  vinay
khattar
11          11       would stick to banking  girish pai  centrum
broking
12          12                 msci adds aurobindo pharma to india
```

```
index
13          13                  ashok leyland raises rs crore through
qip
14          14                        at wipro  growth remains a
mirage
15          15          why chinese stocks leave us investors
vulnerable
16          16             us stocks finish mixed amid more tech
selling
17          17                opec reduces estimate on oil demand
growth
18          18                oil prices mixed ahead of us supply
report
19          19                        makemytrip expands share sale
plan
20          20                          gur closes quiet on some
support
21          21                           gur closes steady on low
demand
22          22                           gur closes steady on thin
trade
23          23                       gur remains flat in tight
movements
24          24                popularising g secs among retail
investors
25          25                    gold trades nearly flat on dull
demand
26          26          zee announces closure of share buyback
programme
27          27                                    zee q2 net at rs 3
cr
28          28                    china to start yuan trading on
tuesday
29          29               bse inks strategic partnership with yes
bank

    score
0     0.0
1     0.0
2     1.0
3     1.0
4     0.0
5     0.0
6     1.0
7     0.0
8     0.0
9     1.0
10    0.0
11    1.0
```

```
12    1.0
13    1.0
14   -1.0
15   -1.0
16   -1.0
17   -1.0
18    0.0
19    0.0
20    0.0
21    0.0
22    0.0
23    0.0
24    0.0
25    0.0
26    0.0
27    0.0
28    0.0
29    0.0
```

Ön İşleme Sonrası İlk 30 Satır:

Unnamed: 0		text	score
0	0	spicejet issue crore warrant promoter	0.0
1	1	mmtc q net loss r crore	0.0
2	2	mid cap fund deliver stay put expert	1.0
3	3	mid cap turn market darling	1.0
4	4	market seeing patience conviction prakash diwan	0.0
5	5	infosys strong volume growth sustain	0.0
6	6	hudco raise r cr via tax free bond	1.0
7	7	hoec could retest level ashwani gujral	0.0
8	8	genpact appoints edward j fitzpatrick cfo	0.0
9	9	exl beat profit estimate cut sale outlook	1.0
10	10	wait watch bharti airtel vinay khattar	0.0
11	11	would stick banking girish pai centrum broking	1.0
12	12	msci add aurobindo pharma india index	1.0
13	13	ashok leyland raise r crore qip	1.0
14	14	wipro growth remains mirage	-1.0
15	15	chinese stock leave u investor vulnerable	-1.0
16	16	u stock finish mixed amid tech selling	-1.0
17	17	opec reduces estimate oil demand growth	-1.0
18	18	oil price mixed ahead u supply report	0.0
19	19	makemytrip expands share sale plan	0.0
20	20	gur close quiet support	0.0
21	21	gur close steady low demand	0.0
22	22	gur close steady thin trade	0.0
23	23	gur remains flat tight movement	0.0
24	24	popularising g sec among retail investor	0.0
25	25	gold trade nearly flat dull demand	0.0
26	26	zee announces closure share buyback programme	0.0
27	27	zee q net r cr	0.0

```
28          28                  china start yuan trading tuesday    0.0
29          29           bse ink strategic partnership yes bank    0.0
```

```
df['Comment']=df['text'].apply(str)

X = []
sentences = list(df['Comment'])
for sen in sentences:
    X.append(clean_text(sen))

df
```


```
{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 21862,\n  \"fields\":
[\n    {\n      \"column\": \"Unnamed: 0\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 6311,\n        \"min\": 0,\n
\"max\": 21861,\n        \"num_unique_values\": 21862,\n
\"samples\": [\n          7886,\n          12956,\n          20484\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"text\",\n      \"properties\":
{\n        \"dtype\": \"string\",\n        \"num_unique_values\":
15858,\n        \"samples\": [\n          \"first nine month
talvivaara net loss narrowed eur million eur million period\",\n
\"hindalco plunge q net profit shrink\",\n          \"nikkei edge
cyclical share sold trading thin event\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"score\",\n      \"properties\": {\
n        \"dtype\": \"number\",\n        \"std\": 0.7300226654189315,\
n        \"min\": -1.0,\n        \"max\": 1.0,\n
\"num_unique_values\": 3,\n        \"samples\": [\n          0.0,\n
1.0,\n          -1.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Comment\",\n      \"properties\": {\n        \"dtype\": \"string\",\
n        \"num_unique_values\": 15858,\n        \"samples\": [\n
\"first nine month talvivaara net loss narrowed eur million eur
million period\",\n          \"hindalco plunge q net profit shrink\",\
n          \"nikkei edge cyclical share sold trading thin event\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\n}","type":"dataframe","variable_name":"df"}
```


italik metin####### %30-70

```
y=df['score']



X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42, stratify=y)

from sklearn import  preprocessing
encoder = preprocessing.LabelEncoder()
```

```
y_train = encoder.fit_transform(y_train)
y_test = encoder.fit_transform(y_test)

#feature extraction with Tf-idf vectorizer

#feature extraction with BOW
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(max_features=12000)
vectorizer.fit(X_train)

train_vectors = vectorizer.transform(X_train)
test_vectors = vectorizer.transform(X_test)
print(train_vectors.shape, test_vectors.shape)
```

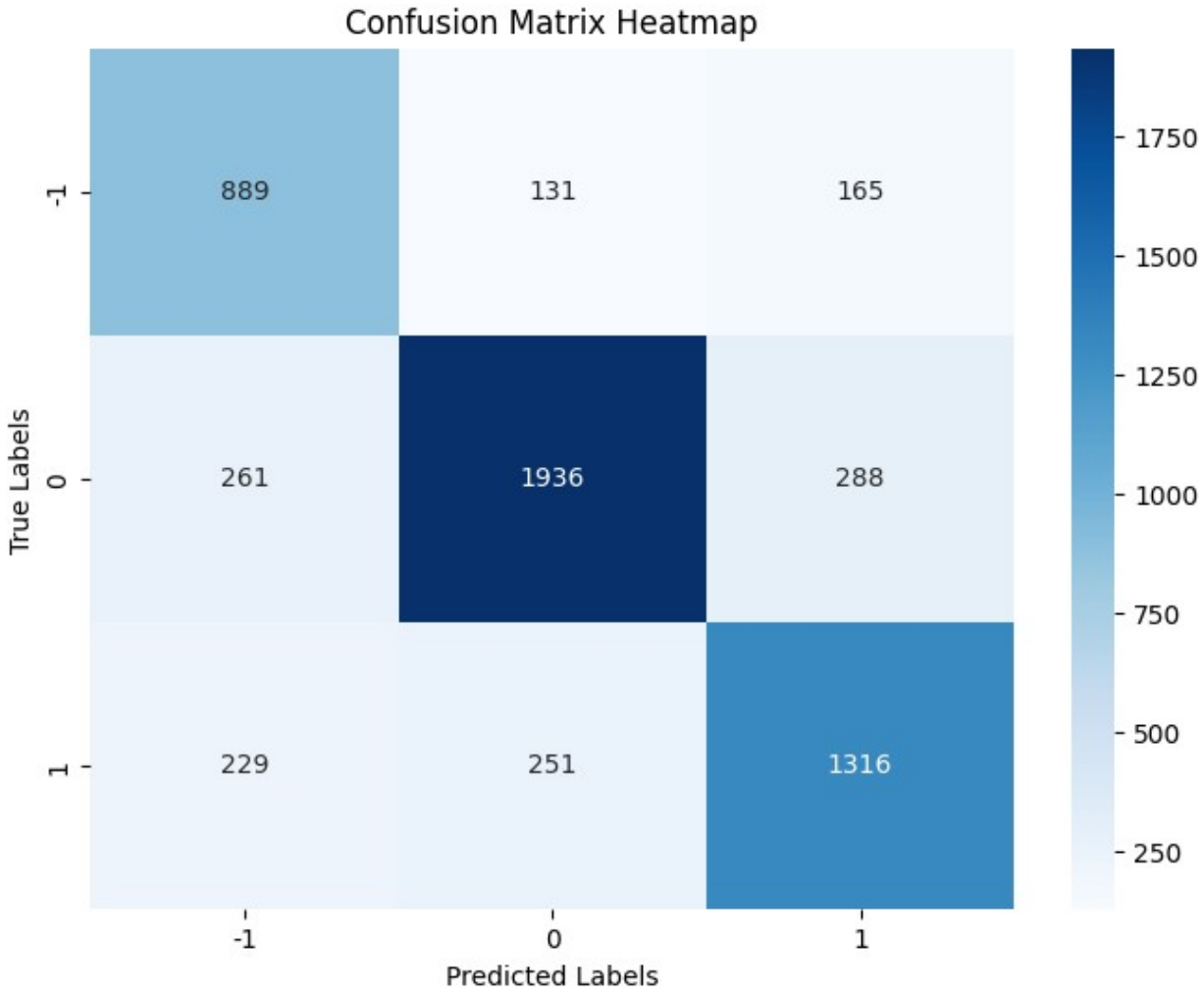
```
(15303, 12000) (6559, 12000)
```

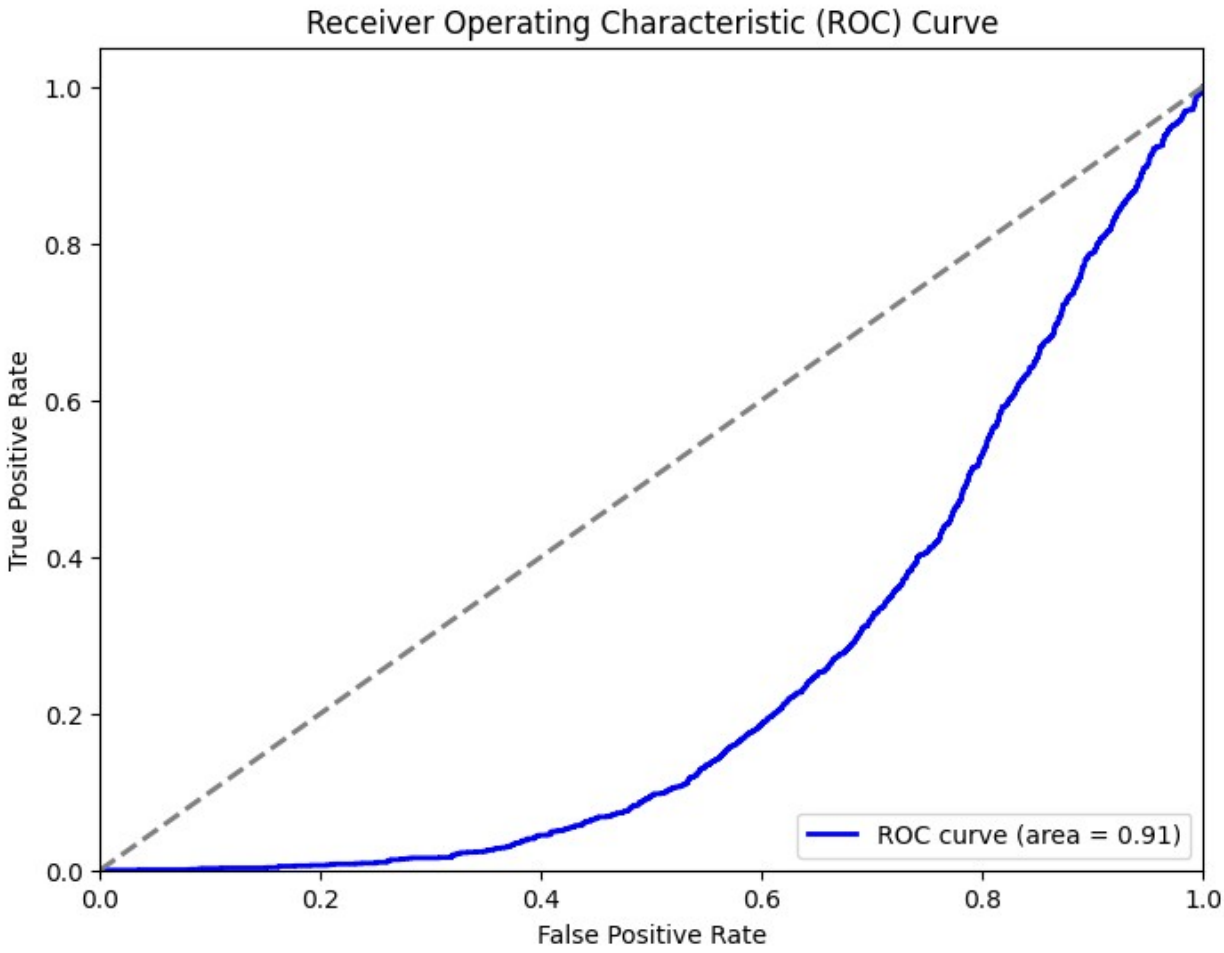
```
import pandas as pd
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.naive_bayes import MultinomialNB
from imblearn.over_sampling import SMOTE
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix, roc_auc_score, roc_curve
import seaborn as sns
import matplotlib.pyplot as plt

# Veriyi yükleyin (df['text'] ve df['score']'dan)
# X = df['text']
# y = df['score']

# Veriyi eğitim ve test setlerine ayıralım
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42, stratify=y)

# TF-IDF Vektörleştirme
vectorizer = TfidfVectorizer(stop_words='english', ngram_range=(1, 2),
max_features=12000)
X_train_vec = vectorizer.fit_transform(X_train)
X_test_vec = vectorizer.transform(X_test)

# SMOTE ile Veri Dengeleme (k_neighbors parametresi ile)
smote = SMOTE(random_state=42, k_neighbors=5)  # k_neighbors=5
X_train_res, y_train_res = smote.fit_resample(X_train_vec, y_train)

# Naive Bayes Modeli
nb = MultinomialNB().fit(X_train_res, y_train_res)  # Yalnızca eğitim
verileri ile model eğitildi

# Hiperparametre Optimasyonu (Grid Search)
param_grid = {
    'alpha': [0.1, 0.2, 0.5, 1.0],  # L2 Regularization için alpha
```

```
parametresi
}

grid_search = GridSearchCV(nb, param_grid, cv=5, scoring='accuracy',
verbose=1)
grid_search.fit(X_train_res, y_train_res)

# En iyi parametreleri yazdırma
print(f"Best parameters: {grid_search.best_params_}")

# Modeli test seti ile değerlendirme
y_pred = grid_search.best_estimator_.predict(X_test_vec)
accuracy = accuracy_score(y_test, y_pred)

# Sonuçları yazdırma
print(f'Accuracy: {accuracy:.4f}')
print("Classification Report:\n", classification_report(y_test,
y_pred))

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

# Confusion Matrix'i Heatmap ile Görselleştirme
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['-1',
'0', '1'], yticklabels=['-1', '0', '1'])
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()

# ROC AUC Değeri ve Eğrisi
roc_auc = roc_auc_score(y_test,
grid_search.best_estimator_.predict_proba(X_test_vec),
multi_class='ovr')
fpr, tpr, _ = roc_curve(y_test,
grid_search.best_estimator_.predict_proba(X_test_vec)[:, 1],
pos_label=1)

# ROC AUC Eğrisini Görselleştirme
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
```

```
plt.legend(loc='lower right')
plt.show()
```

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits
Best parameters: {'alpha': 0.1}
Accuracy: 0.7576
Classification Report:
              precision    recall  f1-score   support

        -1.0       0.64      0.75      0.69      1185
         0.0       0.84      0.78      0.81      2485
         1.0       0.74      0.73      0.74      1796

    accuracy                           0.76      5466
   macro avg       0.74      0.75      0.75      5466
weighted avg       0.76      0.76      0.76      5466
```





BOW

NB

SVM

```
#eğitim ve test oranı %80 -%20 olarak ayarlandı

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42, stratify=y)
from sklearn import  preprocessing
encoder = preprocessing.LabelEncoder()
y_train = encoder.fit_transform(y_train)
y_test = encoder.fit_transform(y_test)

#feature extraction with Tf-idf vectorizer

#feature extraction with BOW
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(max_features=10800)
vectorizer.fit(X_train)

train_vectors = vectorizer.transform(X_train)
```

```
test_vectors = vectorizer.transform(X_test)
print(train_vectors.shape, test_vectors.shape)
```

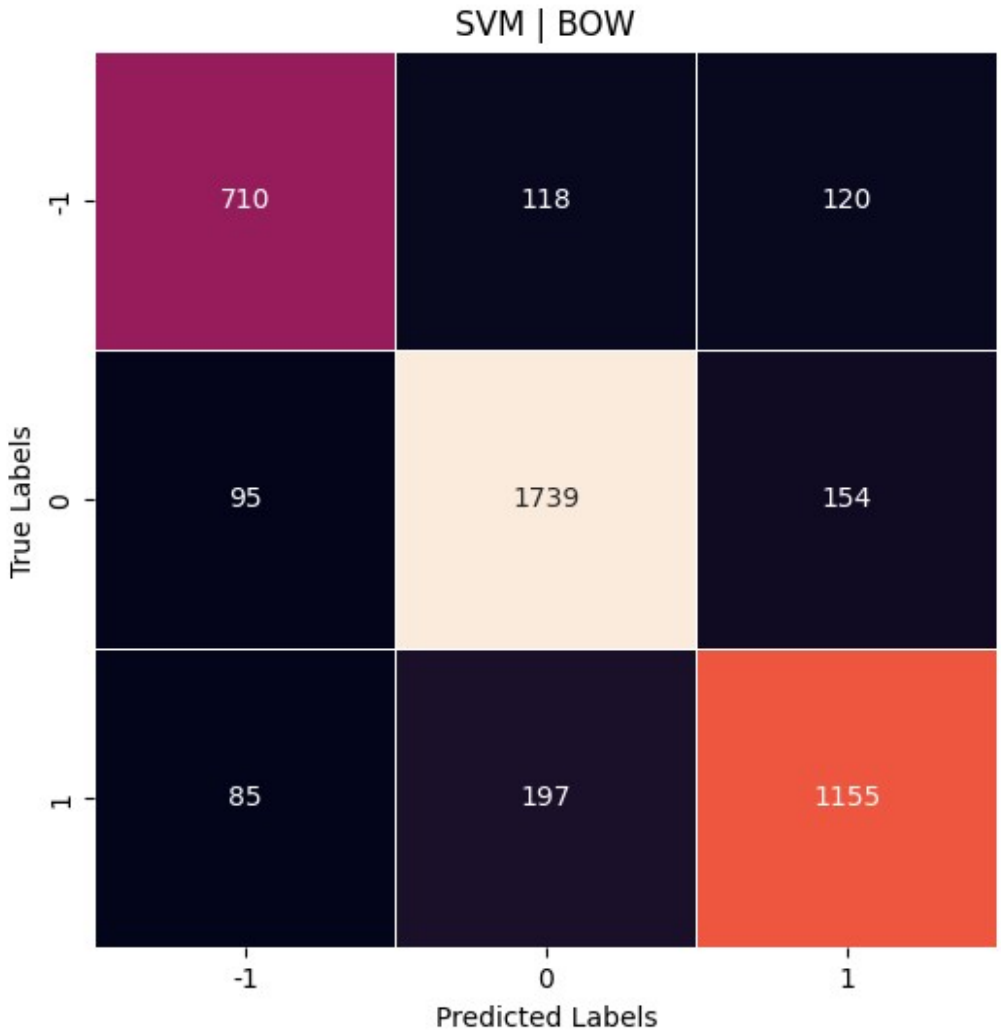
```
(17489, 10800) (4373, 10800)
```

```
from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score, classification_report

# Model eğitimi
l2_norm = 2
l2_norm_inverse = 1 / l2_norm
maximum_iterations = 4000
svm = LinearSVC(C=l2_norm_inverse, max_iter=maximum_iterations)
SVM = svm.fit(train_vectors, y_train)

# Test verileri üzerinde tahmin
predictions_SVM = SVM.predict(test_vectors)

# Doğruluk skoru
print("SVM Accuracy Score -> ", accuracy_score(predictions_SVM,
y_test) * 100)

# Sınıfların doğru görünmesi için classification_report düzeltmesi
target_names = ['-1', '0', '1']  # Sınıf isimlerini doğru şekilde
belirtin
print(classification_report(y_test, predictions_SVM,
target_names=target_names))
```

```
SVM Accuracy Score ->  82.41481820260691
              precision    recall  f1-score   support

          -1       0.80      0.75      0.77       948
           0       0.85      0.87      0.86      1988
           1       0.81      0.80      0.81      1437

    accuracy                           0.82      4373
   macro avg       0.82      0.81      0.81      4373
weighted avg       0.82      0.82      0.82      4373
```

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Confusion matrix
cm = confusion_matrix(y_test, predictions_SVM)

# Görselleştirme
plt.figure(figsize=(6, 6))
plt.title("SVM | BOW")
sns.heatmap(cm, annot=True, fmt="d", linewidths=0.5, cbar=False,
```

```
            xticklabels=["-1", "0", "1"], yticklabels=["-1", "0",
"1"])
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```



LOG REG

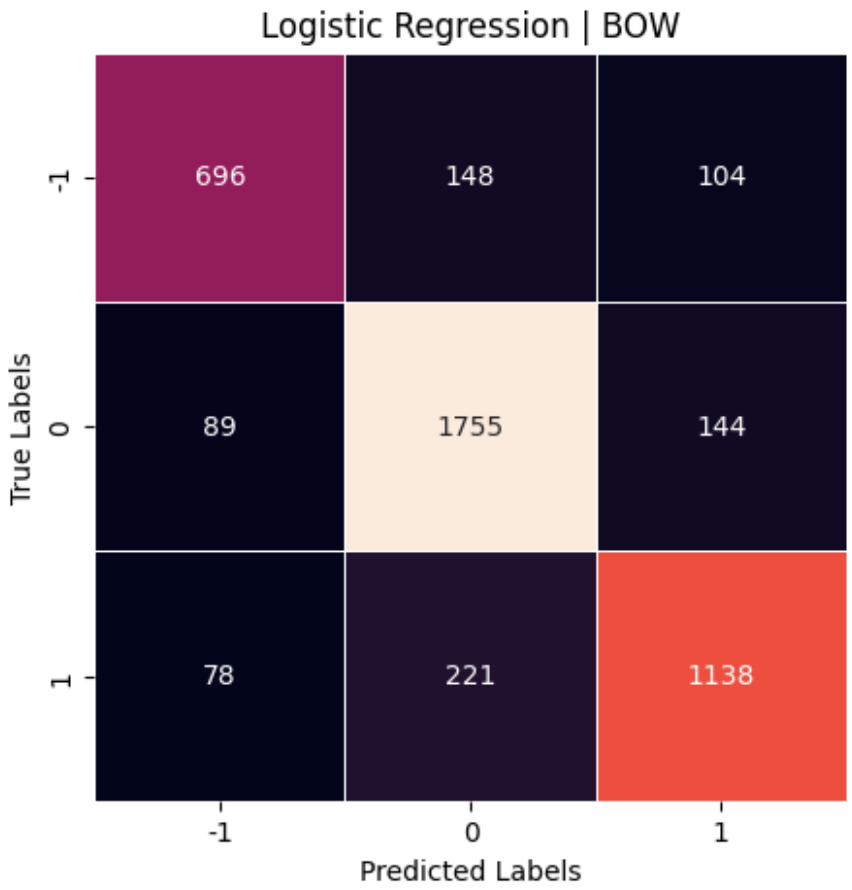
```
from sklearn import linear_model
from sklearn.model_selection import cross_val_score
log_reg = linear_model.LogisticRegression()
log_reg.fit(train_vectors,y_train)
predictions_log = log_reg.predict(test_vectors)
print("Logistic Regression Accuracy Score ->
",accuracy_score(predictions_log, y_test)*100)
```

```
Logistic Regression Accuracy Score ->  82.07180425337297
```

```python
from sklearn.metrics import classification_report

# Sınıfları yeniden adlandırma
target_names = ["-1", "0", "1"]

# classification_report ile etiketleri özelleştirme
print(classification_report(y_test, predictions_log,
target_names=target_names))
```

```
              precision    recall  f1-score   support

          -1       0.81      0.73      0.77       948
           0       0.83      0.88      0.85      1988
           1       0.82      0.79      0.81      1437

    accuracy                           0.82      4373
   macro avg       0.82      0.80      0.81      4373
weighted avg       0.82      0.82      0.82      4373
```

```python
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Confusion matrix
cm = confusion_matrix(y_test, predictions_log)

# Görselleştirme
plt.figure(figsize=(5, 5))
plt.title("Logistic Regression | BOW")
sns.heatmap(cm, annot=True, fmt="d", linewidths=0.5, cbar=False,
            xticklabels=["-1", "0", "1"], yticklabels=["-1", "0",
"1"])
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```



Decission Tree

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
tree_clf = DecisionTreeClassifier()
tree_clf.fit(train_vectors, y_train)
predictions_tree = tree_clf.predict(test_vectors)
print("Decision Tree Accuracy Score -> ",
accuracy_score(predictions_tree, y_test) * 100)
```

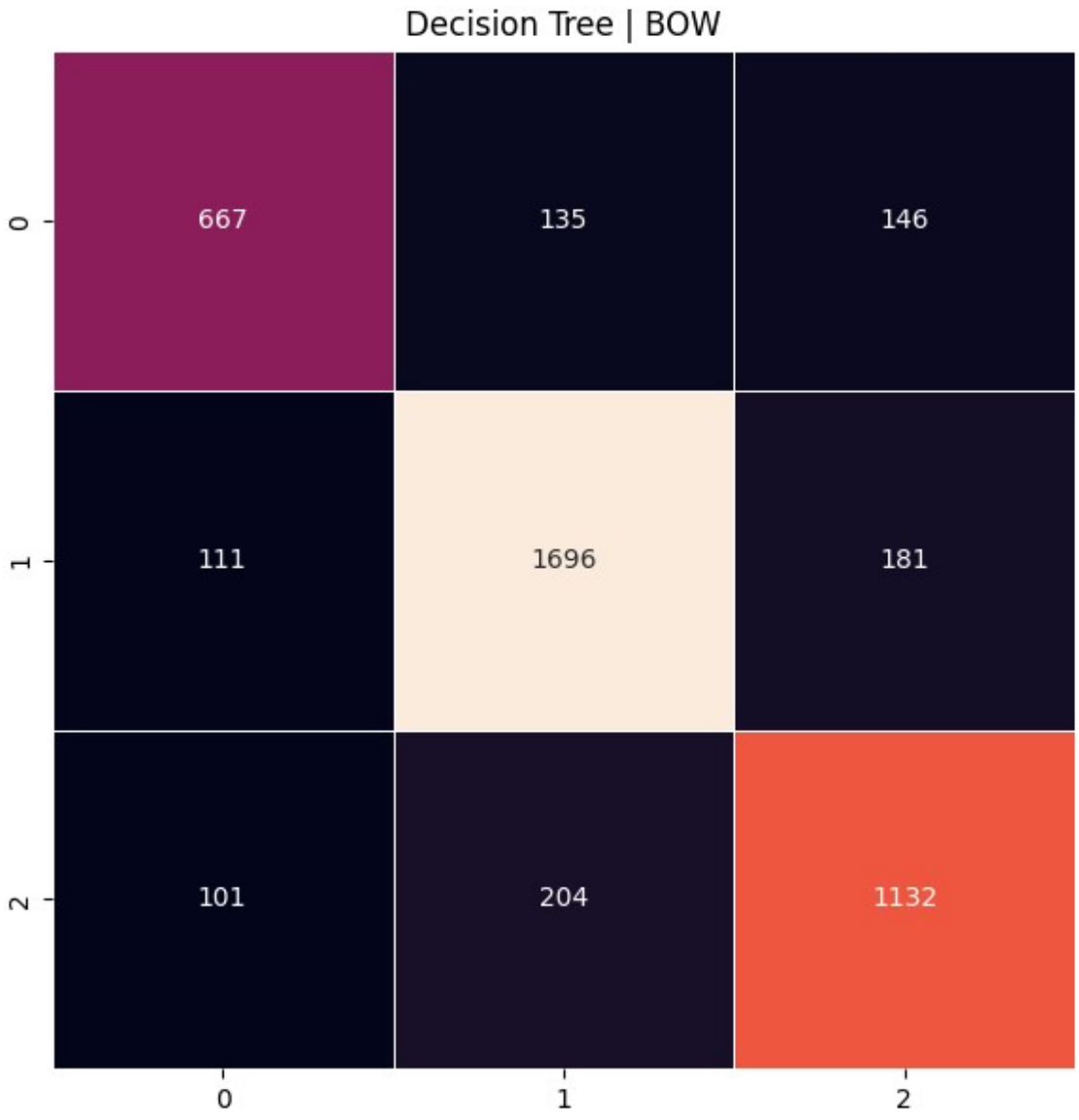
```
Decision Tree Accuracy Score ->  79.92225017150697
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, predictions_tree))
```

```
              precision    recall  f1-score   support

        -1.0       0.76      0.70      0.73       948
         0.0       0.83      0.85      0.84      1988
         1.0       0.78      0.79      0.78      1437

    accuracy                           0.80      4373
   macro avg       0.79      0.78      0.79      4373
```

```
weighted avg       0.80      0.80      0.80      4373
```

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Karar ağacı modeli için confusion matrix oluştur
cm_tree = confusion_matrix(y_test, predictions_tree)

# Heatmap'i çiz
plt.figure(figsize=(7,7))
plt.title("Decision Tree | BOW")
sns.heatmap(cm_tree, annot=True, fmt="d", linewidths=0.7 ,cbar=False)
plt.show()
```



Random forest

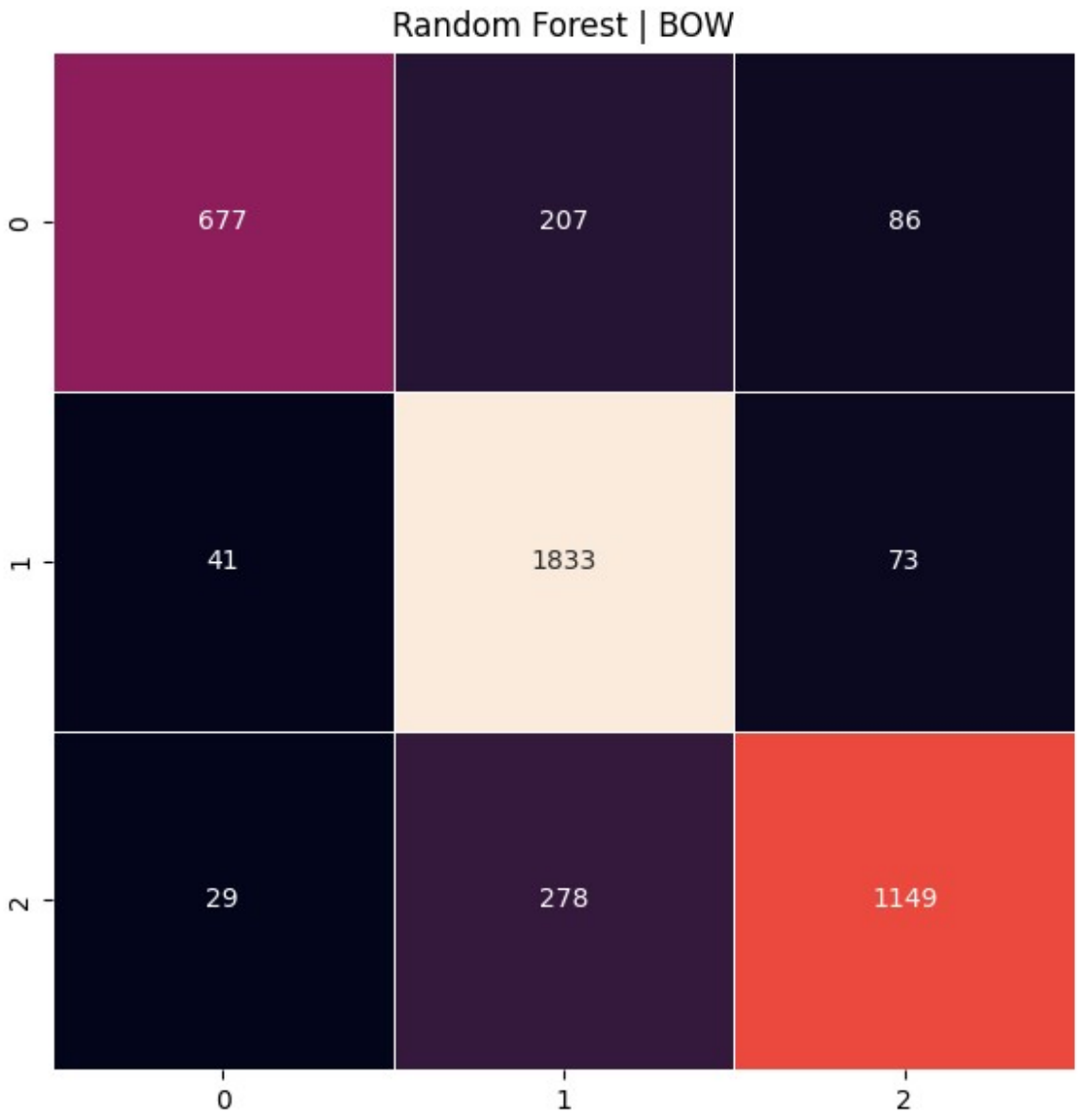
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Random Forest sınıflandırıcısını tanımla
rf_clf = RandomForestClassifier()

# Modeli eğit
rf_clf.fit(train_vectors, y_train)

# Test verileri üzerinde tahmin yap
predictions_rf = rf_clf.predict(test_vectors)

# Doğruluk skorunu hesapla ve yazdır
print("Random Forest Accuracy Score -> ",
accuracy_score(predictions_rf, y_test) * 100)
```

```
Random Forest Accuracy Score ->  83.67253601646468
```

```
from sklearn.metrics import classification_report

# Sınıflandırma raporunu yazdır
print(classification_report(y_test, predictions_rf))
```

```
              precision    recall  f1-score   support

           0       0.91      0.70      0.79       970
           1       0.79      0.94      0.86      1947
           2       0.88      0.79      0.83      1456

    accuracy                           0.84      4373
   macro avg       0.86      0.81      0.83      4373
weighted avg       0.85      0.84      0.83      4373
```

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Random Forest modeli için confusion matrix oluştur
cm_rf = confusion_matrix(y_test, predictions_rf)

# Heatmap'i çiz
plt.figure(figsize=(7,7))
plt.title("Random Forest | BOW")
sns.heatmap(cm_rf, annot=True, fmt="d", linewidths=0.7 ,cbar=False)
plt.show()
```



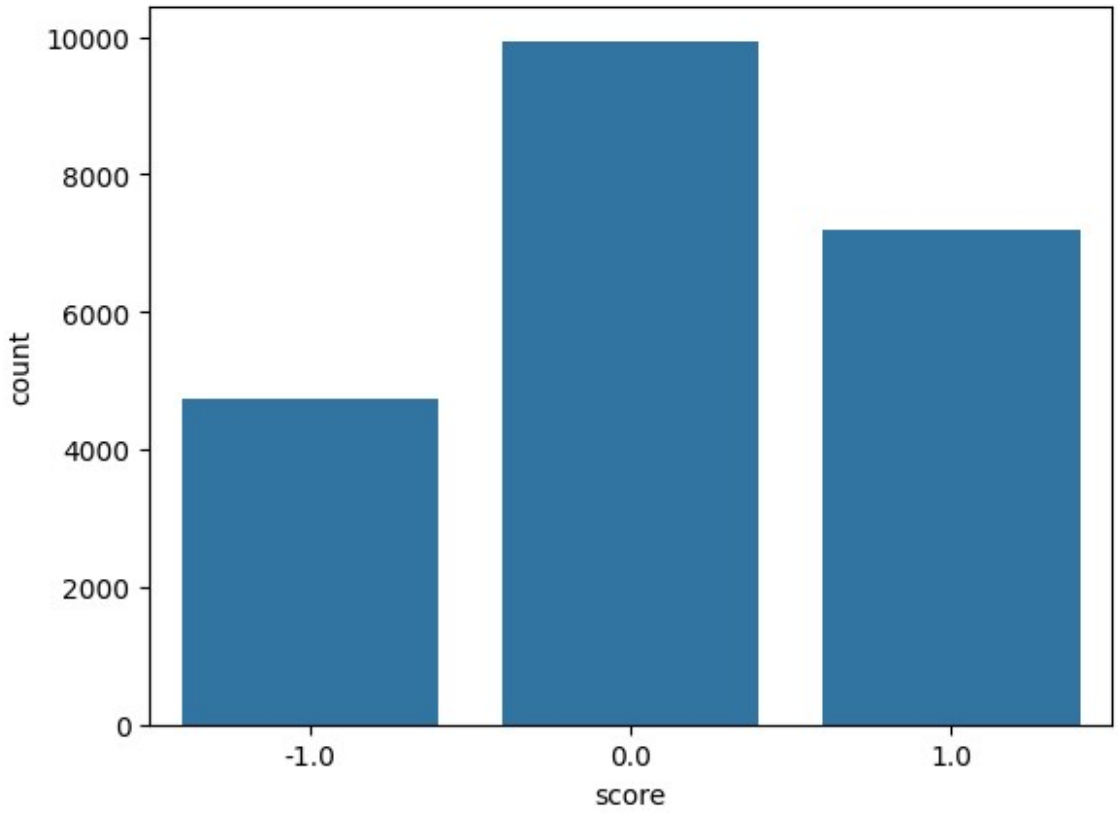
- TF_IDF
  - NB
  - SVM
  - KNN
  - LOGISTIC REG

######Kütüphanelerin Yüklenmesi

```
df=pd.read_csv("cleaned_df.csv",index_col=0)
```

```
import seaborn as sns
sns.countplot(x='score', data=df)
```

```
<Axes: xlabel='score', ylabel='count'>
```




```
X = []
# Assuming 'text' is the column containing the text data
sentences = list(df['text'])
for sen in sentences:
    X.append(clean_text(sen))

y = df['score']

y.shape
```

```
(21862,)
```

%30-70

```
  X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.30, random_state=42 ,stratify=y)
```

TF-IDF

```
#feature extraction with Tf-idf vectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(max_features=8000)
train_vectors = vectorizer.fit_transform(X_train)
test_vectors = vectorizer.transform(X_test)
print(train_vectors.shape, test_vectors.shape)
```

```
(15303, 8000) (6559, 8000)
```

```
print(test_vectors)
```

```
  (0, 764) 0.47036966769617644
  (0, 1268)     0.16091229277405242
  (0, 2150)     0.18630891886460182
  (0, 2559)     0.2733369025385488
  (0, 2730)     0.10874529389457414
  (0, 3226)     0.07181787973354006
  (0, 3800)     0.47912949285521106
  (0, 3802)     0.27021066946873545
  (0, 3924)     0.2623004042824456
  (0, 4165)     0.2842666156183621
  (0, 4625)     0.22117262165547408
  (0, 5020)     0.14568278056854303
  (0, 6012)     0.19155821581518226
  (0, 6657)     0.21296573187898987
  (0, 7147)     0.06601177831065894
  (0, 7933)     0.13310518679928887
  (1, 355) 0.15046862519425008
  (1, 819) 0.4425487812883377
  (1, 1956)     0.34064753377257095
  (1, 2004)     0.34656743649935967
  (1, 2226)     0.3592681041147897
  (1, 3418)     0.1927431110480928
  (1, 3776)     0.4136621193907689
  (1, 4460)     0.25635970966316046
  (1, 5886)     0.3772266049168742
  :   :
  (6556, 4678)  0.16464480937884704
  (6556, 6606)  0.4080871493041005
  (6556, 6734)  0.3941908528539454
  (6556, 7735)  0.34720610659055207
  (6557, 937)   0.40543934226747025
  (6557, 1762)  0.28288192350424424
  (6557, 5178)  0.5543797612833016
  (6557, 5579)  0.4661312953369391
  (6557, 6091)  0.25140472279851933
  (6557, 7181)  0.40960605249170395
  (6558, 70)    0.2615217062441849
```

```
  (6558, 103)   0.2960839268372882
  (6558, 1025)  0.30978996952007554
  (6558, 2918)  0.184142197298422
  (6558, 3561)  0.35110626928374666
  (6558, 4532)  0.2596683506763168
  (6558, 4625)  0.09579574116477062
  (6558, 5026)  0.2767233571950661
  (6558, 5236)  0.2615217062441849
  (6558, 5716)  0.2849018406319152
  (6558, 6543)  0.2825112816410467
  (6558, 6986)  0.3847106863744229
  (6558, 7147)  0.17154873460037742
  (6558, 7222)  0.09006095512543684
  (6558, 7822)  0.15062896200966863
```

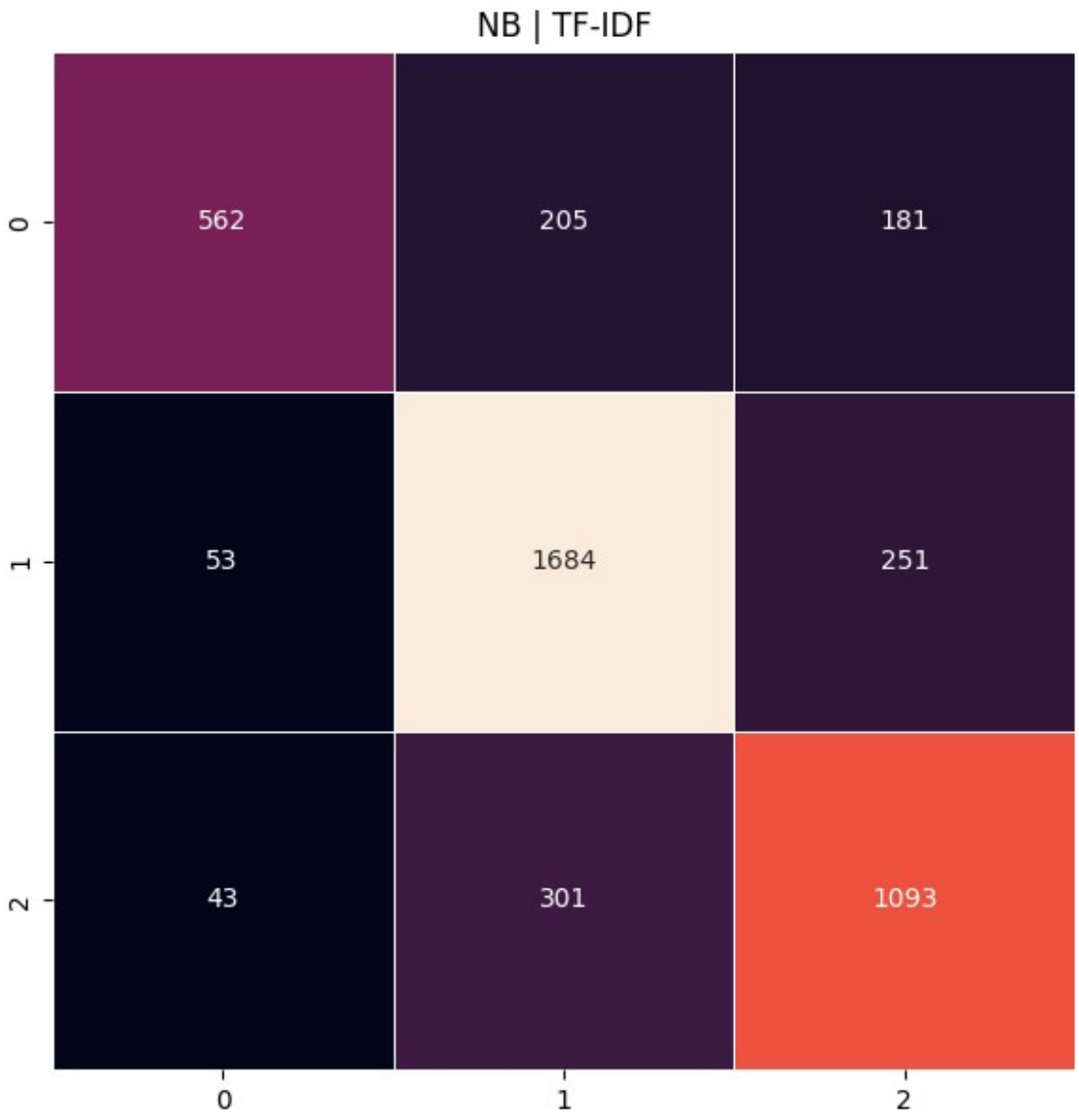
NB

```
  X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.25, random_state=42 ,stratify=y)

# Cell 96: TF-IDF Vectorization
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

# Cell 100: Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42 ,stratify=y)

# Cell 96 (Continued): Fit vectorizer AFTER train-test split
vectorizer = TfidfVectorizer(max_features=8000)
train_vectors = vectorizer.fit_transform(X_train) # Now X_train is the
correct one from the split
test_vectors = vectorizer.transform(X_test)
print(train_vectors.shape, test_vectors.shape)

# Cell 101: Model Training (No changes needed here)
from sklearn.naive_bayes import MultinomialNB
clf = MultinomialNB().fit(train_vectors, y_train)

(17489, 8000) (4373, 8000)

#test the performance of our model on the test set to predict the
sentiment labels
from  sklearn.metrics  import accuracy_score
predicted = clf.predict(test_vectors)
print("Naive Bayes Accuracy Score -> ",
accuracy_score(y_test,predicted)*100)

Naive Bayes Accuracy Score ->  76.35490509947405
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, predicted))
```

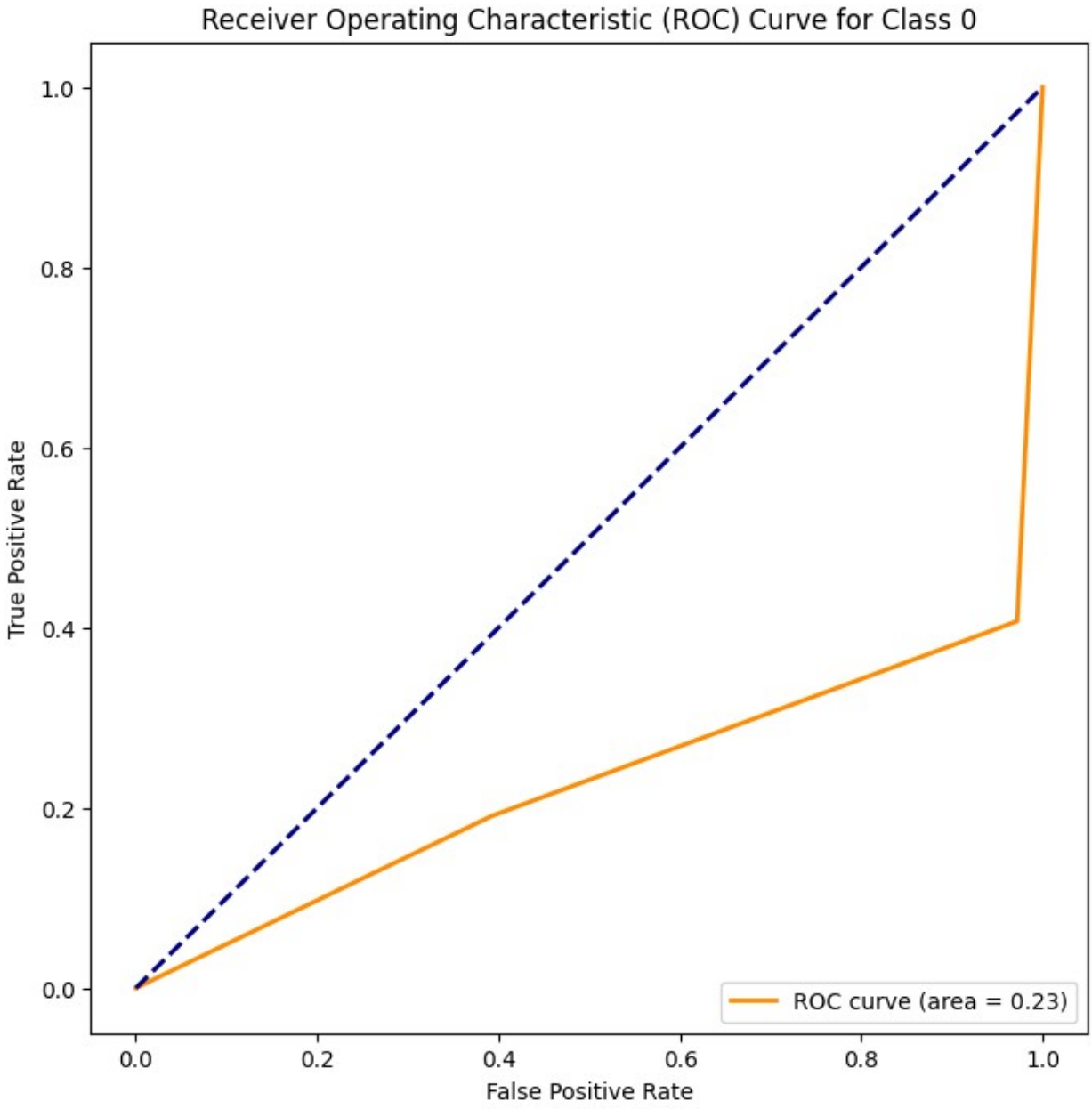
```
              precision    recall  f1-score   support

        -1.0       0.85      0.59      0.70       948
         0.0       0.77      0.85      0.81      1988
         1.0       0.72      0.76      0.74      1437

    accuracy                           0.76      4373
   macro avg       0.78      0.73      0.75      4373
weighted avg       0.77      0.76      0.76      4373
```

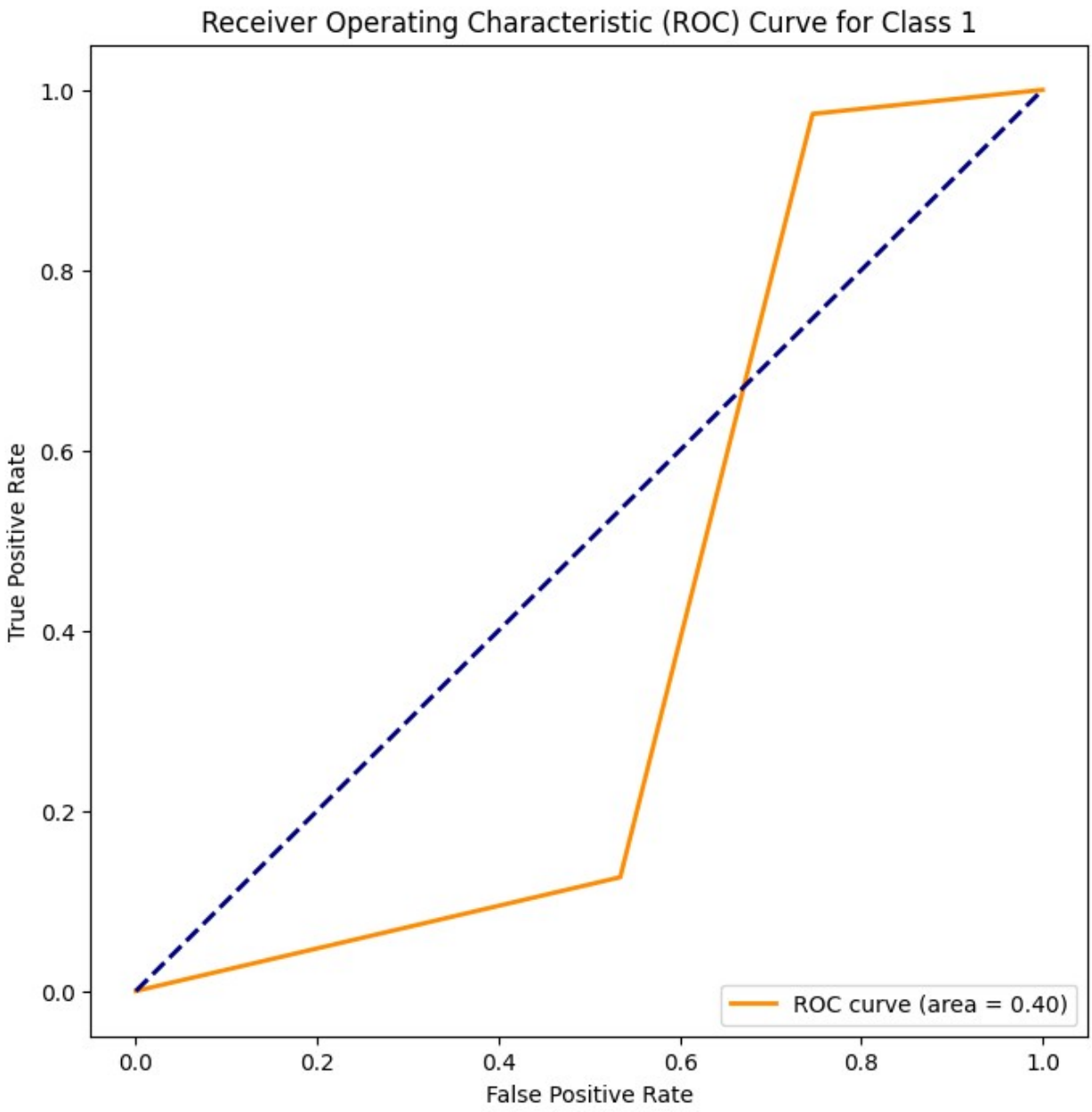
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, predicted)
plt.figure(figsize=(7,7))
plt.title("NB | TF-IDF")
sns.heatmap(cm, annot=True, fmt="d", linewidths=0.7 ,cbar=False)
plt.show()
```

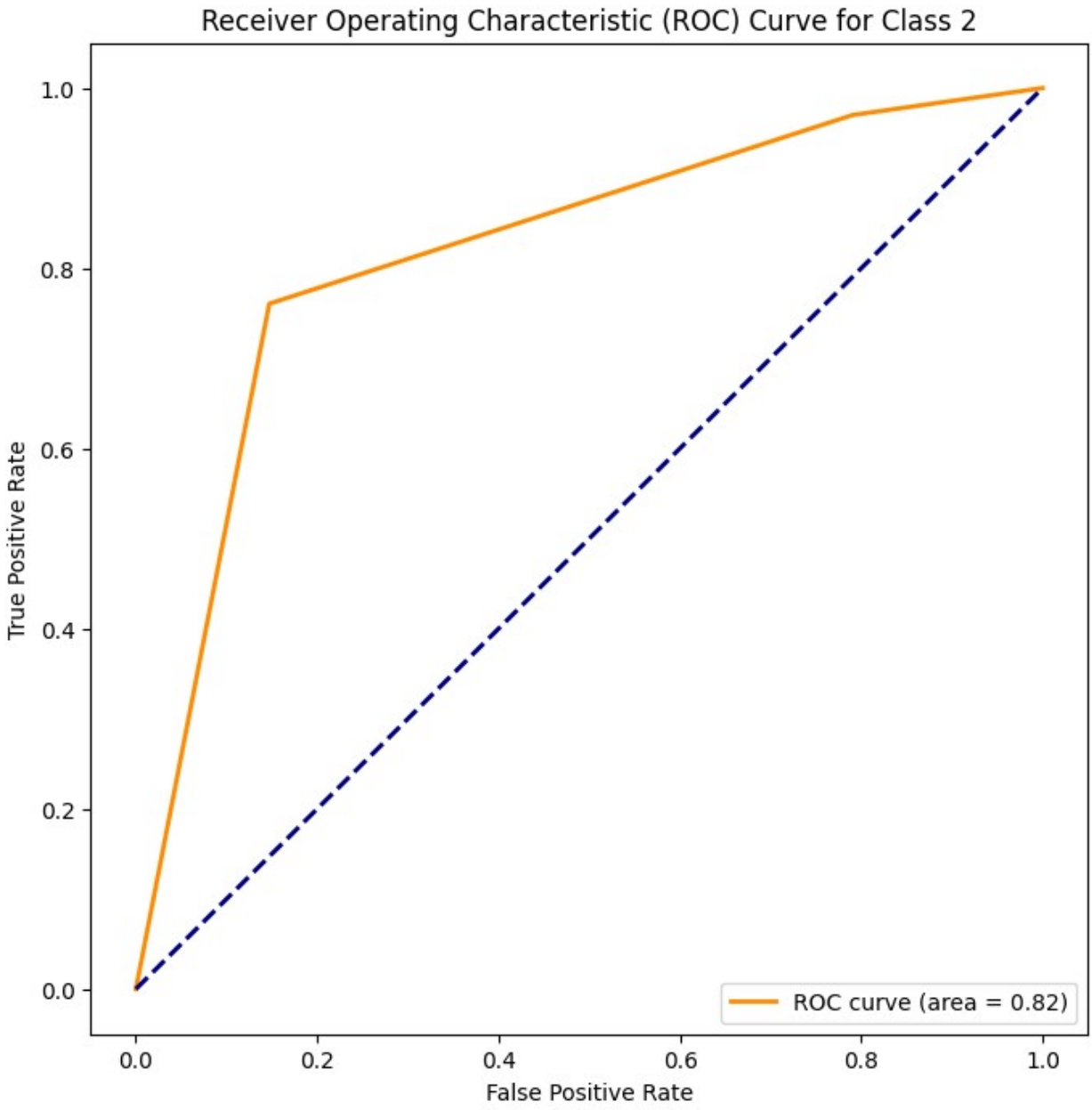



```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
from sklearn.preprocessing import label_binarize

# Assuming you have already imported necessary libraries and have
y_test, predicted

# Binarize the multiclass labels
y_test_binarized = label_binarize(y_test, classes=np.unique(y_test))

# Iterate through each class and plot the ROC curve
for i in range(y_test_binarized.shape[1]):
    fpr, tpr, _ = roc_curve(y_test_binarized[:, i], predicted) #
Assuming 'predicted' contains probabilities for the current class
```

```
    roc_auc = auc(fpr, tpr)

    plt.figure(figsize=(8, 8))
    plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve
(area = {:.2f})'.format(roc_auc))
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'Receiver Operating Characteristic (ROC) Curve for
Class {i}')
    plt.legend(loc='lower right')
    plt.show()
```




Receiver Operating Characteristic (ROC) Curve for Class 1
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (area = 0.40)



SVM

```
from sklearn.svm import LinearSVC
l2_norm = 1
l2_norm_inverse = 1/l2_norm
maximum_iterations=4500 #maximum number of iterations
svm = LinearSVC(C=l2_norm_inverse,max_iter=maximum_iterations) #create
support vector machine model

SVM=svm.fit(train_vectors,y_train)
```

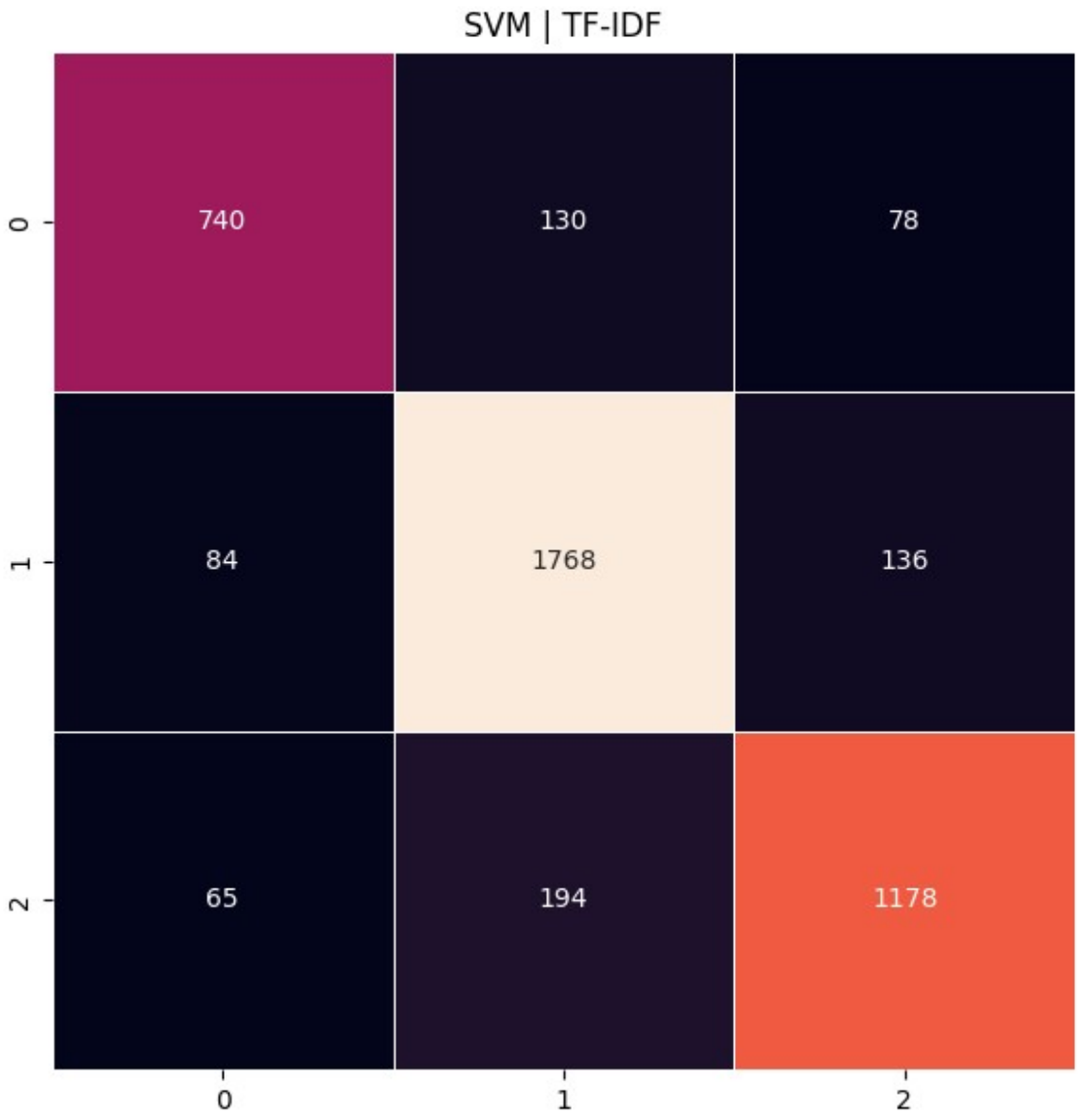
```
# predict the labels on validation dataset
predictions_SVM = SVM.predict(test_vectors)
# Use accuracy_score function to get the accuracy
print("SVM Accuracy Score -> ",accuracy_score(predictions_SVM,
y_test)*100)
```

```
SVM Accuracy Score ->  84.28996112508575
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, predictions_SVM))
```

```
              precision    recall  f1-score   support

        -1.0       0.83      0.78      0.81       948
         0.0       0.85      0.89      0.87      1988
         1.0       0.85      0.82      0.83      1437

    accuracy                           0.84      4373
   macro avg       0.84      0.83      0.84      4373
weighted avg       0.84      0.84      0.84      4373
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, predictions_SVM)
plt.figure(figsize=(7,7))
plt.title("SVM | TF-IDF")
sns.heatmap(cm, annot=True, fmt="d", linewidths=0.7 ,cbar=False)
plt.show()
```



Logistic Regresion

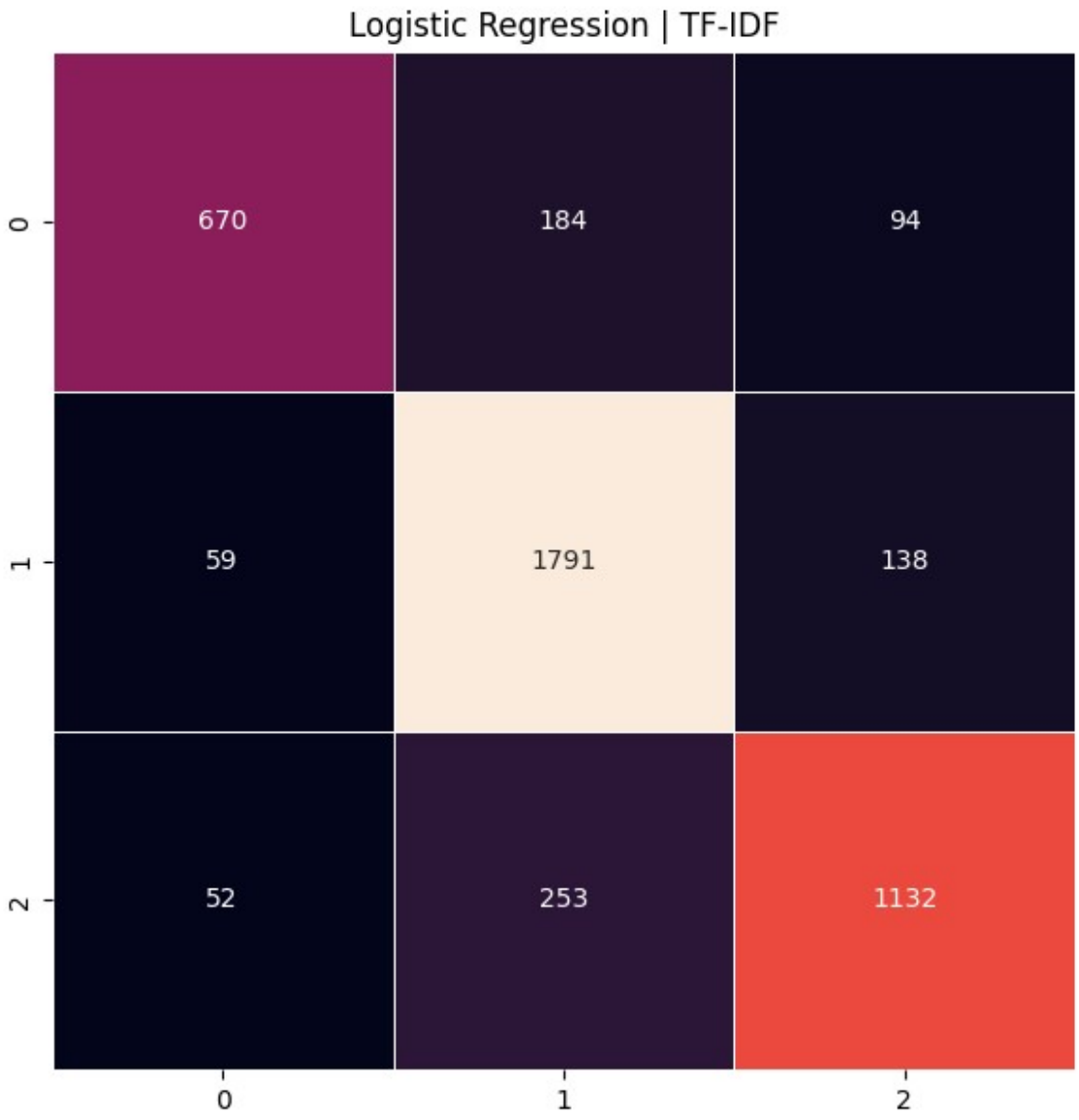
```
from sklearn import linear_model
from sklearn.model_selection import cross_val_score
log_reg = linear_model.LogisticRegression()
log_reg.fit(train_vectors,y_train)
predictions_log = log_reg.predict(test_vectors)
print("Logistic Regression Accuracy Score ->
",accuracy_score(predictions_log, y_test)*100)
```

```
Logistic Regression Accuracy Score ->  82.16327463983535
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, predictions_log))
```

```
              precision    recall  f1-score   support

        -1.0       0.86      0.71      0.78       948
         0.0       0.80      0.90      0.85      1988
         1.0       0.83      0.79      0.81      1437

    accuracy                           0.82      4373
   macro avg       0.83      0.80      0.81      4373
weighted avg       0.82      0.82      0.82      4373
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, predictions_log)
plt.figure(figsize=(7,7))
plt.title("Logistic Regression | TF-IDF")
sns.heatmap(cm, annot=True, fmt="d", linewidths=0.7 ,cbar=False)
plt.show()
```



KNN

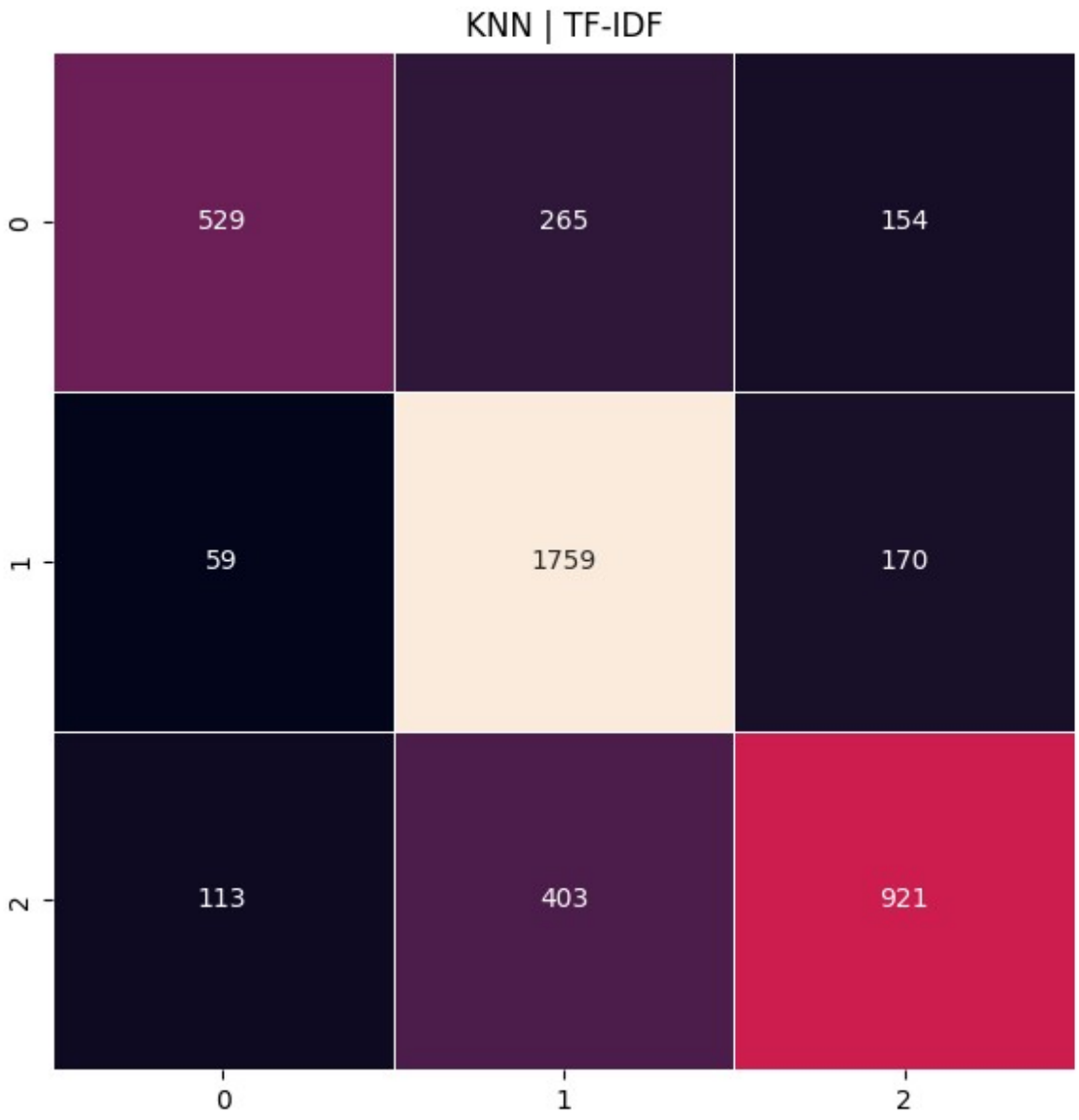
```
from sklearn.neighbors import KNeighborsClassifier
number_of_neigbors = 27
minkowski_power = 2 # Manhattan Distance = 1, Euclidean Distance = 2
knn = KNeighborsClassifier(n_neighbors=number_of_neigbors, p
=minkowski_power)
model_knn=knn.fit(train_vectors, y_train)
predictions_knn = model_knn.predict(test_vectors)
print("KNN Accuracy Score -> ",accuracy_score(predictions_knn,
y_test)*100)
```

```
KNN Accuracy Score ->  73.3821175394466
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, predictions_knn))
```

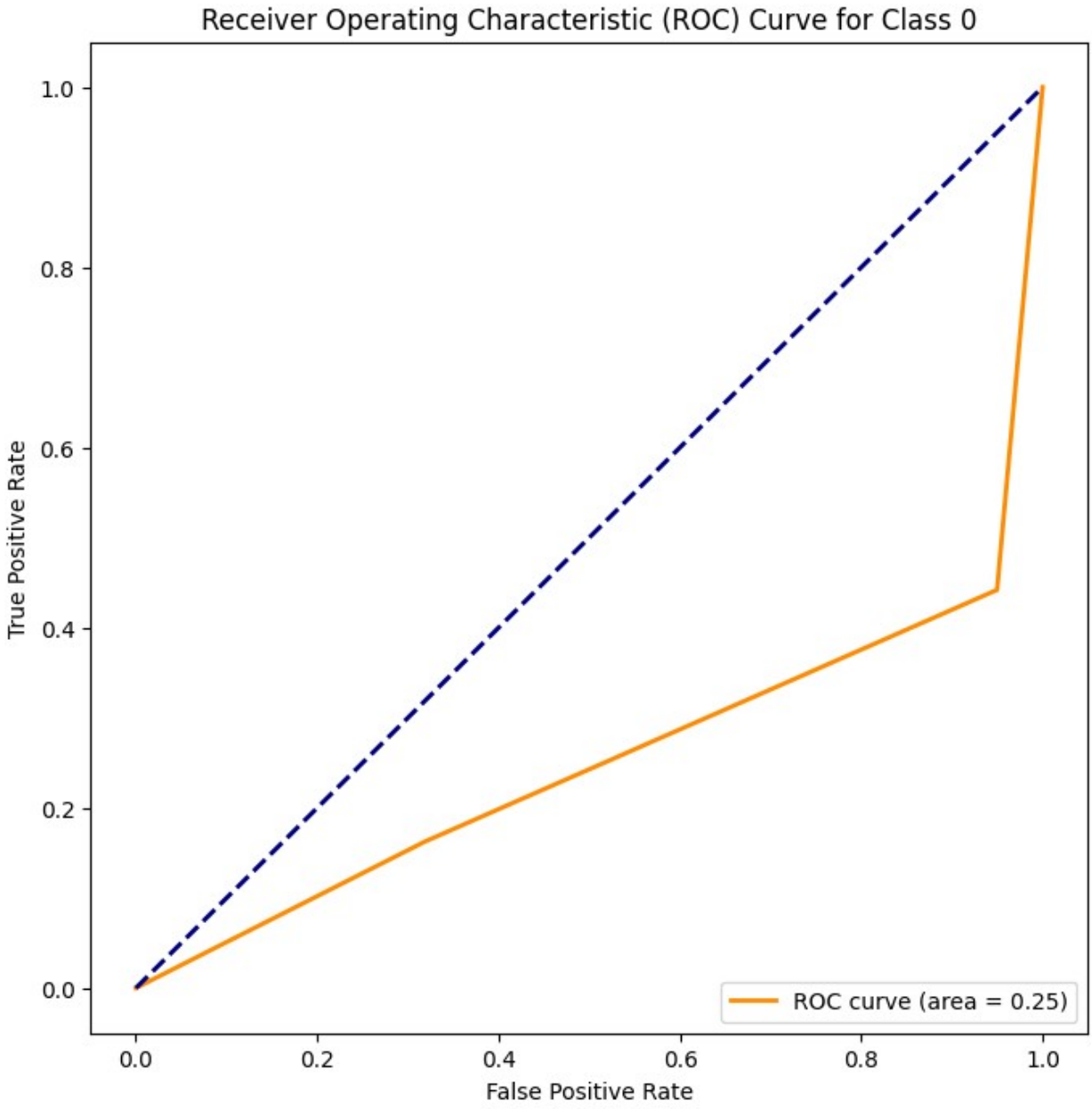
```
              precision    recall  f1-score   support

        -1.0       0.75      0.56      0.64       948
         0.0       0.72      0.88      0.80      1988
         1.0       0.74      0.64      0.69      1437

    accuracy                           0.73      4373
   macro avg       0.74      0.69      0.71      4373
weighted avg       0.74      0.73      0.73      4373
```

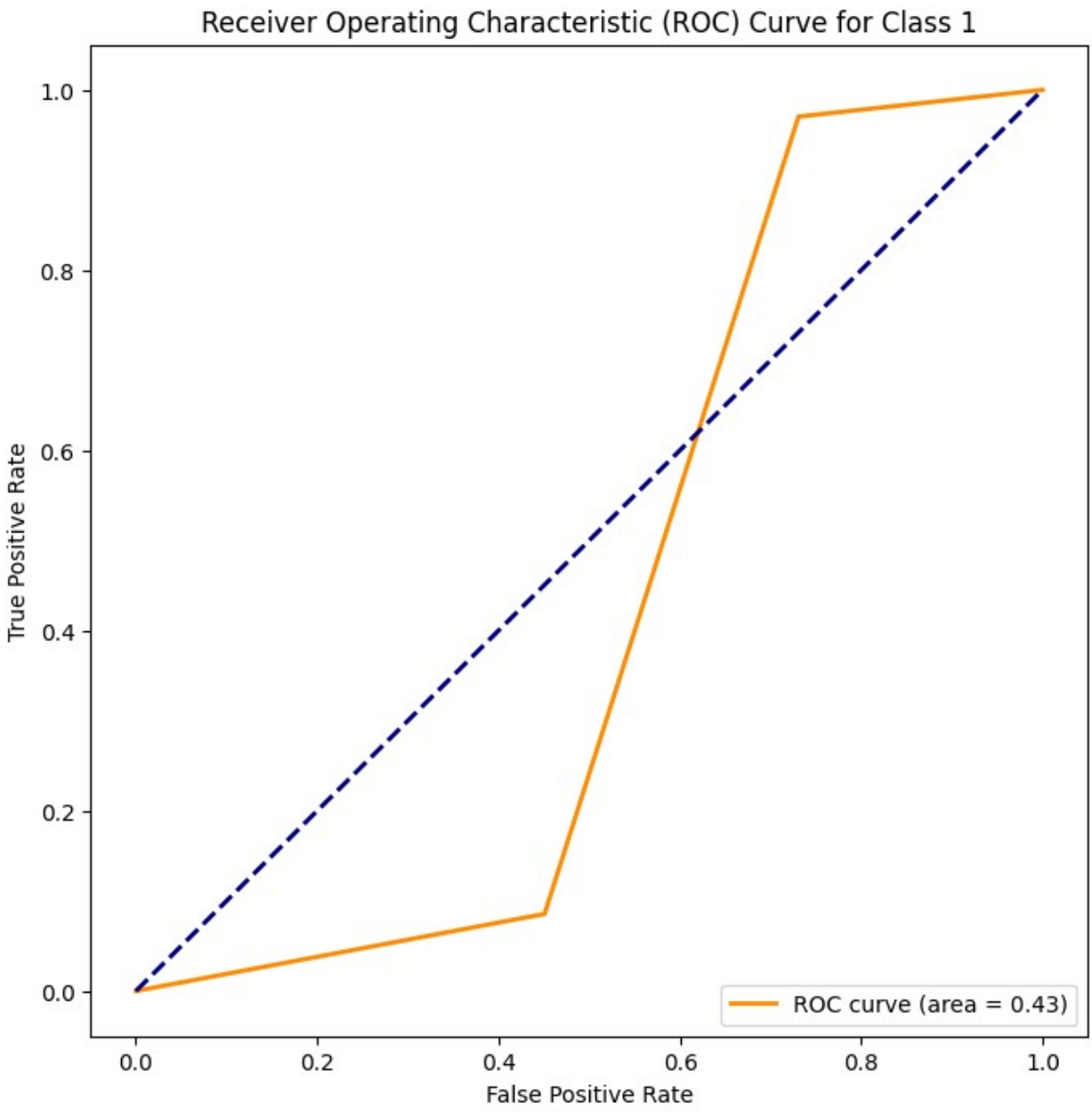
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, predictions_knn)
plt.figure(figsize=(7,7))
plt.title("KNN | TF-IDF")
sns.heatmap(cm, annot=True, fmt="d", linewidths=0.7 ,cbar=False)
plt.show()
```

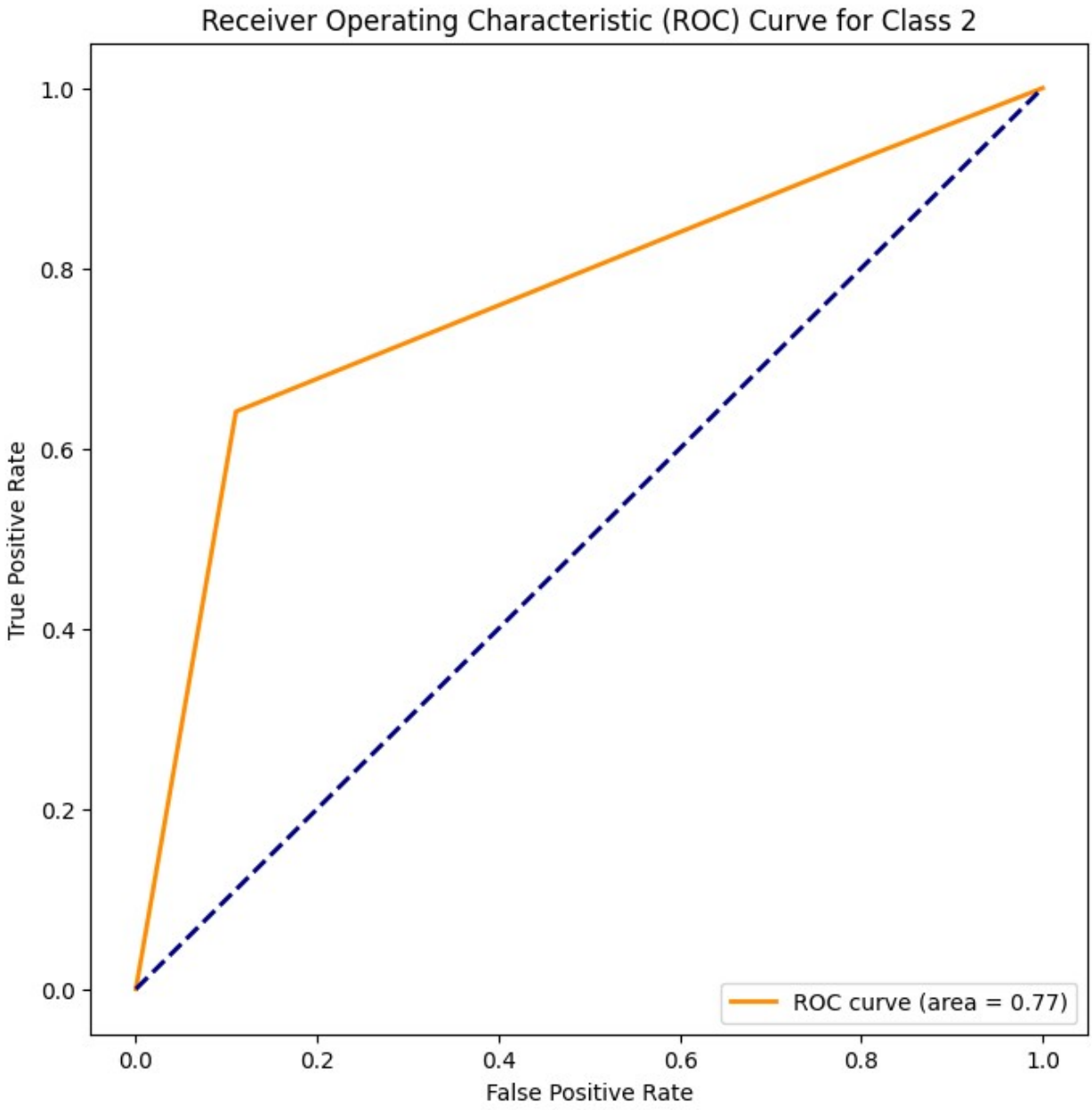



```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
from sklearn.preprocessing import label_binarize

# Binarize the multiclass labels
y_test_binarized = label_binarize(y_test, classes=np.unique(y_test))

# Assuming 'predictions_knn' contains probabilities for each class
# If not, use predict_proba to get probabilities
# predictions_knn_proba = model_knn.predict_proba(test_vectors)

# Iterate through each class and plot the ROC curve
for i in range(y_test_binarized.shape[1]):
    fpr, tpr, _ = roc_curve(y_test_binarized[:, i], predictions_knn)
```

```
    roc_auc = auc(fpr, tpr)

    plt.figure(figsize=(8, 8))
    plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve
(area = {:.2f})'.format(roc_auc))
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'Receiver Operating Characteristic (ROC) Curve for
Class {i}')
    plt.legend(loc='lower right')
    plt.show()
```




Receiver Operating Characteristic (ROC) Curve for Class 1
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (area = 0.43)



Decision tree

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

# Decision Tree sınıflandırıcısını tanımla
tree_clf = DecisionTreeClassifier()

# Modeli eğit
tree_clf.fit(train_vectors, y_train)

# Test verileri üzerinde tahmin yap
predictions_tree = tree_clf.predict(test_vectors)
```

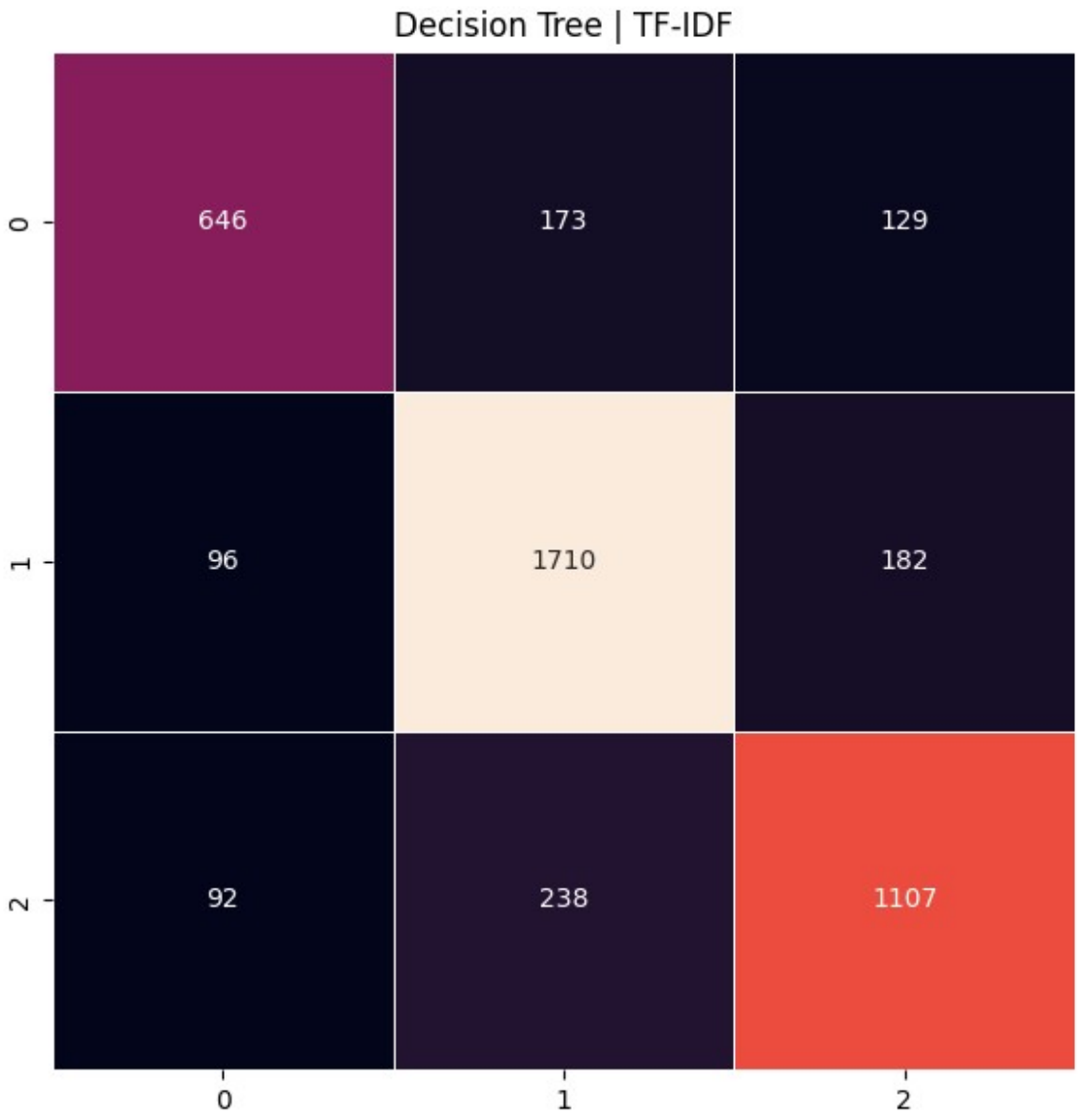
```python
# Doğruluk skorunu hesapla ve yazdır
print("Decision Tree Accuracy Score -> ",
accuracy_score(predictions_tree, y_test) * 100)
```

```
Decision Tree Accuracy Score ->  79.19048707980791
```

```python
from sklearn.metrics import classification_report

# Sınıflandırma raporunu yazdır
print(classification_report(y_test, predictions_tree))
```

```
              precision    recall  f1-score   support

        -1.0       0.77      0.68      0.73       948
         0.0       0.81      0.86      0.83      1988
         1.0       0.78      0.77      0.78      1437

    accuracy                           0.79      4373
   macro avg       0.79      0.77      0.78      4373
weighted avg       0.79      0.79      0.79      4373
```

```python
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Karar ağacı modeli için confusion matrix oluştur
cm_tree = confusion_matrix(y_test, predictions_tree)

# Heatmap'i çiz
plt.figure(figsize=(7,7))
plt.title("Decision Tree | TF-IDF")
sns.heatmap(cm_tree, annot=True, fmt="d", linewidths=0.7 ,cbar=False)
plt.show()
```



######Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Random Forest sınıflandırıcısını tanımla
rf_clf = RandomForestClassifier()

# Modeli eğit
rf_clf.fit(train_vectors, y_train)

# Test verileri üzerinde tahmin yap
predictions_rf = rf_clf.predict(test_vectors)

# Doğruluk skorunu hesapla ve yazdır
```

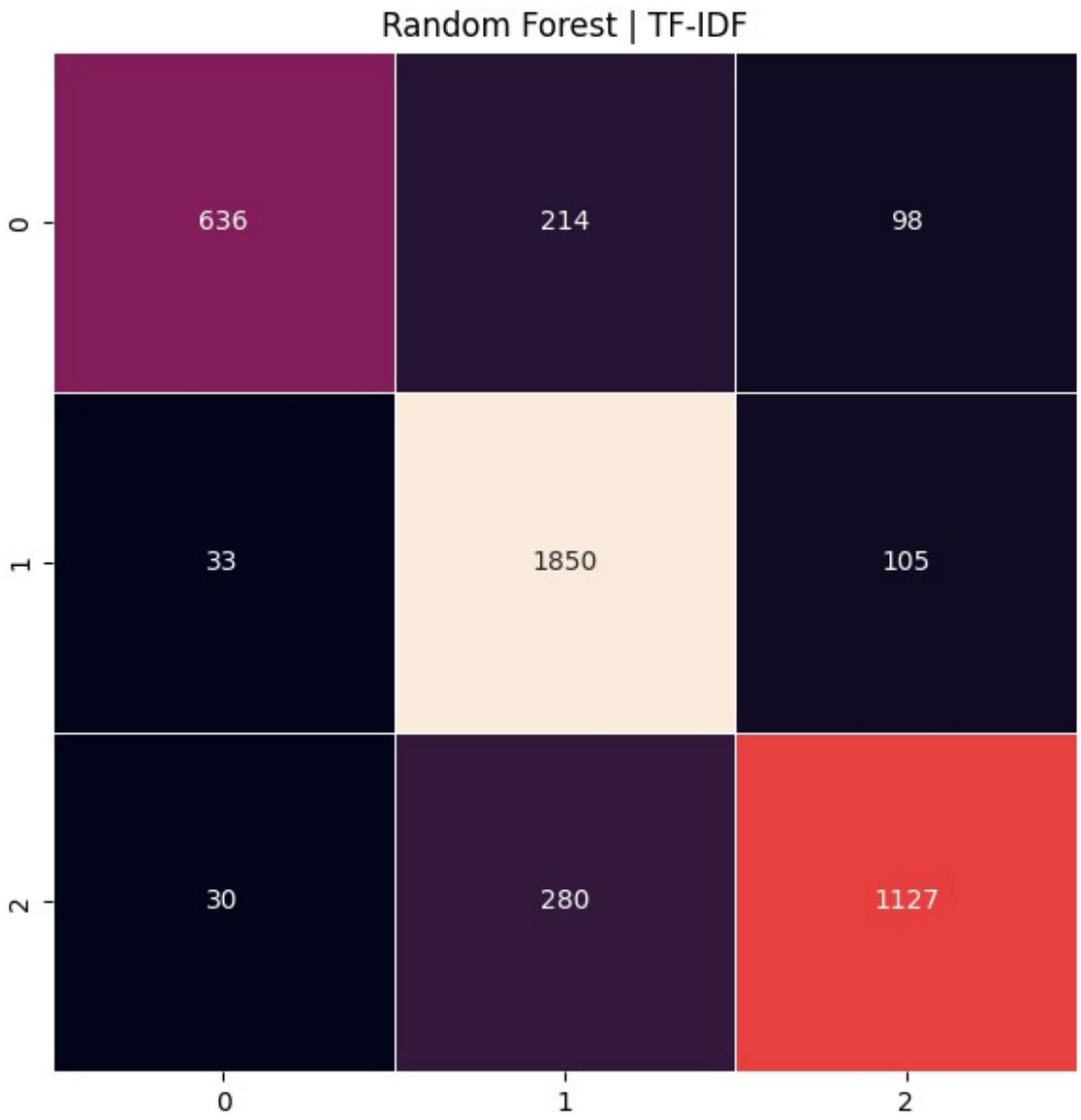
```
print("Random Forest Accuracy Score -> ",
accuracy_score(predictions_rf, y_test) * 100)
```

```
Random Forest Accuracy Score ->  82.62062657214727
```

```
from sklearn.metrics import classification_report

# Sınıflandırma raporunu yazdır
print(classification_report(y_test, predictions_rf))
```

```
              precision    recall  f1-score   support

        -1.0       0.91      0.67      0.77       948
         0.0       0.79      0.93      0.85      1988
         1.0       0.85      0.78      0.81      1437

    accuracy                           0.83      4373
   macro avg       0.85      0.80      0.81      4373
weighted avg       0.83      0.83      0.82      4373
```

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Random Forest modeli için confusion matrix oluştur
cm_rf = confusion_matrix(y_test, predictions_rf)

# Heatmap'i çiz
plt.figure(figsize=(7,7))
plt.title("Random Forest | TF-IDF")
sns.heatmap(cm_rf, annot=True, fmt="d", linewidths=0.7 ,cbar=False)
plt.show()
```




```
##BIRECTIONAL LSTM MODELİ

#düşük sınıfa yüksek ağırlık learning rate=0.001 max features=10000
kernel regularizer=0.05 batch size=16

import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout,
BatchNormalization, Bidirectional
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix, roc_auc_score
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from tensorflow.keras.regularizers import l2

# Hiperparametreler
max_features = 10000  # Maksimum kelime sayısı
max_len = 100  # Maksimum dizi uzunluğu
embedding_dim = 128  # Gömme boyutu


# Tokenizer tanımla ve veriyi dönüştür
tokenizer = Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(X_train)  # X_train metin verisi

# Eğitim ve test verilerini tam sayılara çevir ve sıfırlarla doldur
X_train_seq = tokenizer.texts_to_sequences(X_train)
X_test_seq = tokenizer.texts_to_sequences(X_test)
X_train_pad = pad_sequences(X_train_seq, maxlen=max_len)
X_test_pad = pad_sequences(X_test_seq, maxlen=max_len)

# One-hot encoding ile etiketleri dönüştür
y_train_onehot = to_categorical(y_train, num_classes=3)
y_test_onehot = to_categorical(y_test, num_classes=3)

# Sınıf ağırlıklarını belirleyin (dengesiz sınıflar için)
class_weights = {0: 1., 1: 2., -1: 3.}

# LSTM modelini oluştur
model = Sequential([
    Embedding(max_features, embedding_dim, input_length=max_len,
trainable=True),
    Bidirectional(LSTM(128, activation='tanh',
recurrent_activation='sigmoid', kernel_initializer='he_normal',
return_sequences=True, kernel_regularizer=l2(0.01))),
    Bidirectional(LSTM(64, activation='tanh',
recurrent_activation='sigmoid', kernel_initializer='he_normal',
kernel_regularizer=l2(0.05))),
    BatchNormalization(),  # BatchNormalization ekleyin
    Dropout(0.4),
    Dense(3, activation='softmax')  # Softmax aktivasyon ile çoklu
sınıf çıkışı
])

# Öğrenme oranını ayarlayın
optimizer = Adam(learning_rate=0.001)

# Modeli derle
model.compile(optimizer=optimizer, loss='categorical_crossentropy',
metrics=['accuracy'])
```

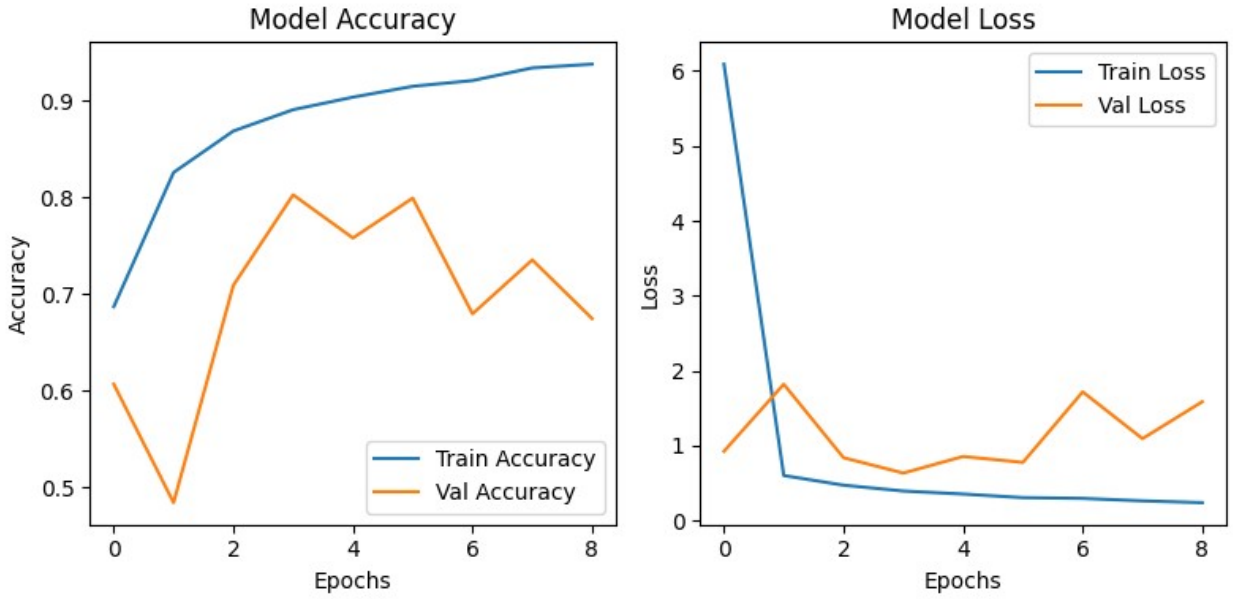
```python
# Erken durdurma ile eğitimi durdurma
early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

# Modeli eğit
history = model.fit(
    X_train_pad, y_train_onehot,  # y_train_onehot çoklu sınıf
etiketlerinin one-hot kodlanmış hali
    epochs=50, batch_size=16,
    validation_split=0.2,
    class_weight=class_weights,  # Sınıf ağırlıklarını ekle
    callbacks=[early_stopping]
)

# Test verileri üzerinde tahmin yap
predictions_rnn = np.argmax(model.predict(X_test_pad), axis=1)  #
Çoklu sınıf tahmini

# Doğruluk skorunu hesapla
accuracy = accuracy_score(np.argmax(y_test_onehot, axis=1),
predictions_rnn)
print(f"LSTM Accuracy Score -> {accuracy * 100:.2f}%")

# Detaylı metrik raporu
print(classification_report(np.argmax(y_test_onehot, axis=1),
predictions_rnn))

# Confusion Matrix
conf_matrix = confusion_matrix(np.argmax(y_test_onehot, axis=1),
predictions_rnn)
print("Confusion Matrix:\n", conf_matrix)

# ROC AUC skoru
roc_auc = roc_auc_score(y_test_onehot, model.predict(X_test_pad),
multi_class='ovr')
print(f"ROC AUC Score: {roc_auc:.4f}")
```

```
Epoch 1/50
875/875 ━━━━━━━━━━━━━━━━━━━━ 297s 326ms/step - accuracy: 0.6173 -
loss: 17.4868 - val_accuracy: 0.6069 - val_loss: 0.9234
Epoch 2/50
875/875 ━━━━━━━━━━━━━━━━━━━━ 312s 315ms/step - accuracy: 0.8338 -
loss: 0.5897 - val_accuracy: 0.4846 - val_loss: 1.8188
Epoch 3/50
875/875 ━━━━━━━━━━━━━━━━━━━━ 330s 325ms/step - accuracy: 0.8764 -
loss: 0.4520 - val_accuracy: 0.7090 - val_loss: 0.8377
Epoch 4/50
875/875 ━━━━━━━━━━━━━━━━━━━━ 314s 316ms/step - accuracy: 0.8981 -
loss: 0.3677 - val_accuracy: 0.8025 - val_loss: 0.6329
```

```
Epoch 5/50
875/875 ━━━━━━━━━━━━━━━━━━━━ 323s 317ms/step - accuracy: 0.9113 -
loss: 0.3260 - val_accuracy: 0.7579 - val_loss: 0.8541
Epoch 6/50
875/875 ━━━━━━━━━━━━━━━━━━━━ 329s 325ms/step - accuracy: 0.9244 -
loss: 0.2834 - val_accuracy: 0.7990 - val_loss: 0.7751
Epoch 7/50
875/875 ━━━━━━━━━━━━━━━━━━━━ 279s 319ms/step - accuracy: 0.9289 -
loss: 0.2743 - val_accuracy: 0.6795 - val_loss: 1.7169
Epoch 8/50
875/875 ━━━━━━━━━━━━━━━━━━━━ 323s 320ms/step - accuracy: 0.9395 -
loss: 0.2365 - val_accuracy: 0.7353 - val_loss: 1.0920
Epoch 9/50
875/875 ━━━━━━━━━━━━━━━━━━━━ 284s 324ms/step - accuracy: 0.9423 -
loss: 0.2203 - val_accuracy: 0.6747 - val_loss: 1.5851
137/137 ━━━━━━━━━━━━━━━━━━━━ 27s 196ms/step
LSTM Accuracy Score -> 78.89%
              precision    recall  f1-score   support

           0       0.83      0.66      0.74       948
           1       0.77      0.90      0.83      1988
           2       0.80      0.72      0.76      1437

    accuracy                           0.79      4373
   macro avg       0.80      0.76      0.77      4373
weighted avg       0.79      0.79      0.79      4373

Confusion Matrix:
 [[ 626  199  123]
 [  63 1793  132]
 [  63  343 1031]]
137/137 ━━━━━━━━━━━━━━━━━━━━ 22s 158ms/step
ROC AUC Score: 0.9169
```

```python
import matplotlib.pyplot as plt

# Eğitim geçmişi doğrulama doğruluğu ve doğrulama kaybını çizme
def plot_training_history(history):
    # Doğrulama doğruluğu eğrisini çiz
    plt.figure(figsize=(8, 4))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Train Accuracy')
    plt.plot(history.history['val_accuracy'], label='Val Accuracy')
    plt.title('Model Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    # Doğrulama kaybı eğrisini çiz
    plt.subplot(1, 2, 2)
```

```
    plt.plot(history.history['loss'], label='Train Loss')
    plt.plot(history.history['val_loss'], label='Val Loss')
    plt.title('Model Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.tight_layout()
    plt.show()

# Eğitim sonrası eğriyi çiz
plot_training_history(history)
```




```
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout,
BatchNormalization, Bidirectional
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix, roc_auc_score
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from tensorflow.keras.regularizers import l2

# Hiperparametreler
max_features = 5000  # Maksimum kelime sayısı
```

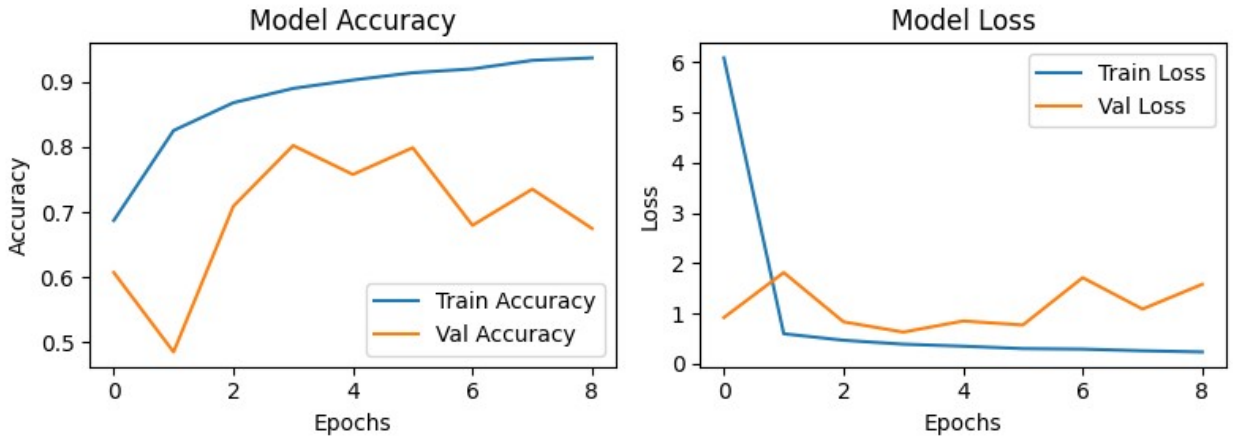
```
max_len = 100  # Maksimum dizi uzunluğu
embedding_dim = 128  # Gömme boyutu

# Veri setinizi hazırlayın (X ve y)
# X_train, X_test ve y_train, y_test veri setlerinin doğru şekilde
tanımlandığından emin olun
# Örnek: X_train = ['metin1', 'metin2', ...], y_train = [-1, 0,
1, ...]

# Tokenizer tanımla ve veriyi dönüştür
tokenizer = Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(X_train)  # X_train metin verisi

# Eğitim ve test verilerini tam sayılara çevir ve sıfırlarla doldur
X_train_seq = tokenizer.texts_to_sequences(X_train)
X_test_seq = tokenizer.texts_to_sequences(X_test)
X_train_pad = pad_sequences(X_train_seq, maxlen=max_len)
X_test_pad = pad_sequences(X_test_seq, maxlen=max_len)

# One-hot encoding ile etiketleri dönüştür
y_train_onehot = to_categorical(y_train, num_classes=3)
y_test_onehot = to_categorical(y_test, num_classes=3)

# Sınıf ağırlıklarını belirleyin (dengesiz sınıflar için)
class_weights = {0: 1., 1: 2., -1: 2.}

# LSTM modelini oluştur
model = Sequential([
    Embedding(max_features, embedding_dim, input_length=max_len,
trainable=True),
    Bidirectional(LSTM(128, activation='tanh',
recurrent_activation='sigmoid', kernel_initializer='he_normal',
return_sequences=True, kernel_regularizer=l2(0.01))),
    Bidirectional(LSTM(64, activation='tanh',
recurrent_activation='sigmoid', kernel_initializer='he_normal',
kernel_regularizer=l2(0.01))),
    BatchNormalization(),  # BatchNormalization ekleyin
    Dropout(0.4),
    Dense(3, activation='softmax')  # Softmax aktivasyon ile çoklu
sınıf çıkışı
])

# Öğrenme oranını ayarlayın
optimizer = Adam(learning_rate=0.0005)

# Modeli derle
model.compile(optimizer=optimizer, loss='categorical_crossentropy',
metrics=['accuracy'])

# Erken durdurma ile eğitimi durdurma
```

```
early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

# Modeli eğit
history = model.fit(
    X_train_pad, y_train_onehot,  # y_train_onehot çoklu sınıf
etiketlerinin one-hot kodlanmış hali
    epochs=50, batch_size=32,
    validation_split=0.2,
    class_weight=class_weights,  # Sınıf ağırlıklarını ekle
    callbacks=[early_stopping]
)

# Test verileri üzerinde tahmin yap
predictions_rnn = np.argmax(model.predict(X_test_pad), axis=1)  #
Çoklu sınıf tahmini

# Doğruluk skorunu hesapla
accuracy = accuracy_score(np.argmax(y_test_onehot, axis=1),
predictions_rnn)
print(f"LSTM Accuracy Score -> {accuracy * 100:.2f}%")

# Detaylı metrik raporu
print(classification_report(np.argmax(y_test_onehot, axis=1),
predictions_rnn))

# Confusion Matrix
conf_matrix = confusion_matrix(np.argmax(y_test_onehot, axis=1),
predictions_rnn)
print("Confusion Matrix:\n", conf_matrix)

# ROC AUC skoru
roc_auc = roc_auc_score(y_test_onehot, model.predict(X_test_pad),
multi_class='ovr')
print(f"ROC AUC Score: {roc_auc:.4f}")

Epoch 1/50
438/438 ━━━━━━━━━━━━━━━━━━━━ 309s 683ms/step - accuracy: 0.6070 -
loss: 18.7989 - val_accuracy: 0.6269 - val_loss: 3.0905
Epoch 2/50
438/438 ━━━━━━━━━━━━━━━━━━━━ 317s 672ms/step - accuracy: 0.8476 -
loss: 1.9078 - val_accuracy: 0.8188 - val_loss: 0.8495
Epoch 3/50
438/438 ━━━━━━━━━━━━━━━━━━━━ 322s 673ms/step - accuracy: 0.8896 -
loss: 0.6349 - val_accuracy: 0.6355 - val_loss: 1.5586
Epoch 4/50
438/438 ━━━━━━━━━━━━━━━━━━━━ 294s 672ms/step - accuracy: 0.9146 -
loss: 0.4179 - val_accuracy: 0.8373 - val_loss: 0.5857
Epoch 5/50
438/438 ━━━━━━━━━━━━━━━━━━━━ 321s 671ms/step - accuracy: 0.9264 -
```

```
loss: 0.3296 - val_accuracy: 0.8213 - val_loss: 0.6561
Epoch 6/50
438/438 ━━━━━━━━━━━━━━━━━━━━ 321s 669ms/step - accuracy: 0.9377 -
loss: 0.2616 - val_accuracy: 0.8242 - val_loss: 0.6556
Epoch 7/50
438/438 ━━━━━━━━━━━━━━━━━━━━ 293s 668ms/step - accuracy: 0.9445 -
loss: 0.2348 - val_accuracy: 0.7301 - val_loss: 1.1027
Epoch 8/50
438/438 ━━━━━━━━━━━━━━━━━━━━ 327s 679ms/step - accuracy: 0.9525 -
loss: 0.1993 - val_accuracy: 0.7679 - val_loss: 1.0161
Epoch 9/50
438/438 ━━━━━━━━━━━━━━━━━━━━ 297s 679ms/step - accuracy: 0.9569 -
loss: 0.1847 - val_accuracy: 0.7776 - val_loss: 1.0155
137/137 ━━━━━━━━━━━━━━━━━━━━ 27s 191ms/step
LSTM Accuracy Score -> 81.93%
              precision    recall  f1-score   support

           0       0.85      0.85      0.85      1988
           1       0.82      0.80      0.81      1437
           2       0.76      0.78      0.77       948

    accuracy                           0.82      4373
   macro avg       0.81      0.81      0.81      4373
weighted avg       0.82      0.82      0.82      4373

Confusion Matrix:
 [[1693  169  126]
 [ 183 1150  104]
 [ 120   88  740]]
137/137 ━━━━━━━━━━━━━━━━━━━━ 23s 171ms/step
ROC AUC Score: 0.9293
```

```python
import matplotlib.pyplot as plt

# Eğitim geçmişi doğrulama doğruluğu ve doğrulama kaybını çizme
def plot_training_history(history):
    # Doğrulama doğruluğu eğrisini çiz
    plt.figure(figsize=(8, 3))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Train Accuracy')
    plt.plot(history.history['val_accuracy'], label='Val Accuracy')
    plt.title('Model Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    # Doğrulama kaybı eğrisini çiz
    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='Train Loss')
    plt.plot(history.history['val_loss'], label='Val Loss')
```

```
    plt.title('Model Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.tight_layout()
    plt.show()

# Eğitim sonrası eğriyi çiz
plot_training_history(history)
```




```
# Doğruluk skorunu hesapla
accuracy = accuracy_score(np.argmax(y_test_onehot, axis=1),
predictions_rnn)
print(f"LSTM Accuracy Score -> {accuracy * 100:.2f}%")
```

```
LSTM Accuracy Score -> 81.93%
```

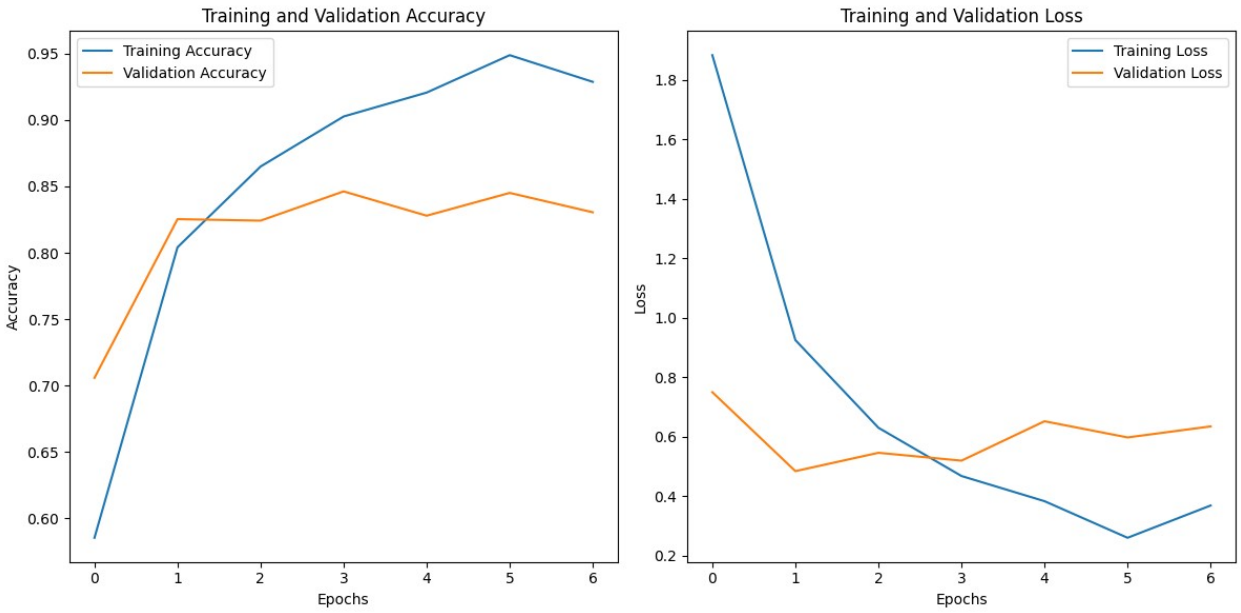
```
#LSTM TABANLI RNN MODELİ

import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense,
Dropout, BatchNormalization, Bidirectional, LSTM
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping,
ReduceLROnPlateau
from sklearn.metrics import accuracy_score, classification_report
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split

# Hiperparametreler
```

```
max_features = 10000  # Kelime sayısını artırarak modelin kelime dağarcığını genişlet
max_len = 150  # Dizi uzunluğunu artırarak daha fazla bilgi kaydedin
embedding_dim = 128  # Gömme boyutunu optimize et
dropout_rate = 0.4  # Dropout oranını %40 olarak ayarla
learning_rate = 0.0005  # Öğrenme oranını küçük tutarak daha stabil eğitim sağla

# Veri setinizi hazırlayın (X ve y)
# X_train, X_test ve y_train, y_test veri setlerinin doğru şekilde tanımlandığından emin olun
# Örnek: X_train = ['metin1', 'metin2', ...], y_train = [-1, 0, 1, ...]

# Tokenizer tanımla ve veriyi dönüştür
tokenizer = Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(X_train)

# Eğitim ve test verilerini tam sayılara çevir ve sıfırlarla doldur
X_train_seq = tokenizer.texts_to_sequences(X_train)
X_test_seq = tokenizer.texts_to_sequences(X_test)
X_train_pad = pad_sequences(X_train_seq, maxlen=max_len)
X_test_pad = pad_sequences(X_test_seq, maxlen=max_len)

# One-hot encoding ile etiketleri dönüştür
y_train_onehot = to_categorical(y_train, num_classes=3)
y_test_onehot = to_categorical(y_test, num_classes=3)

# Sınıf ağırlıklarını belirleyin (dengesiz sınıflar için)
class_weights = {-1: 1., 0: 2., 1: 3.}  # -1 sınıfına 1, 0 sınıfına 2, 1 sınıfına 3 ağırlık atandı

# Modeli oluştur
model = Sequential([
    Embedding(max_features, embedding_dim, input_length=max_len, trainable=True),
    Bidirectional(LSTM(128, activation='tanh', return_sequences=True, kernel_initializer='he_normal', dropout=dropout_rate)),
    Bidirectional(LSTM(64, activation='tanh', kernel_initializer='he_normal', dropout=dropout_rate)),
    BatchNormalization(),  # BatchNormalization ekleyin
    Dropout(dropout_rate),
    Dense(3, activation='softmax')  # Softmax aktivasyon ile çoklu sınıf çıkışı
])

# Öğrenme oranını ayarlayın
optimizer = Adam(learning_rate=learning_rate)

# Modeli derle
```

```
model.compile(optimizer=optimizer, loss='categorical_crossentropy',
metrics=['accuracy'])

# Erken durdurma ile eğitimi durdurma ve Öğrenme oranı düşürme
early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)
lr_scheduler = ReduceLROnPlateau(monitor='val_loss', factor=0.5,
patience=3, min_lr=1e-6)

# Modeli eğit
history = model.fit(
    X_train_pad, y_train_onehot,  # y_train_onehot çoklu sınıf
etiketlerinin one-hot kodlanmış hali
    epochs=60, batch_size=32,
    validation_split=0.2,
    class_weight=class_weights,  # Sınıf ağırlıklarını ekle
    callbacks=[early_stopping, lr_scheduler]
)

# Test verileri üzerinde tahmin yap
predictions_rnn = np.argmax(model.predict(X_test_pad), axis=1)  #
Çoklu sınıf tahmini

# Doğruluk skorunu hesapla
accuracy = accuracy_score(np.argmax(y_test_onehot, axis=1),
predictions_rnn)
print(f"RNN Accuracy Score -> {accuracy * 100:.2f}%")

# Detaylı metrik raporu
print(classification_report(np.argmax(y_test_onehot, axis=1),
predictions_rnn))

# Eğitim süreci doğrulama doğruluğu ve doğrulama kaybı eğrisini çizme
plt.figure(figsize=(12, 6))

# Doğrulama doğruluğu
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Doğrulama kaybı
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
```

```
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

```
Epoch 1/60
438/438 ━━━━━━━━━━━━━━━━━━━━ 460s 1s/step - accuracy: 0.4867 - loss:
2.3964 - val_accuracy: 0.7058 - val_loss: 0.7500 - learning_rate:
5.0000e-04
Epoch 2/60
438/438 ━━━━━━━━━━━━━━━━━━━━ 497s 1s/step - accuracy: 0.7963 - loss:
0.9410 - val_accuracy: 0.8253 - val_loss: 0.4846 - learning_rate:
5.0000e-04
Epoch 3/60
438/438 ━━━━━━━━━━━━━━━━━━━━ 521s 1s/step - accuracy: 0.8668 - loss:
0.6098 - val_accuracy: 0.8242 - val_loss: 0.5462 - learning_rate:
5.0000e-04
Epoch 4/60
438/438 ━━━━━━━━━━━━━━━━━━━━ 499s 1s/step - accuracy: 0.9058 - loss:
0.4441 - val_accuracy: 0.8462 - val_loss: 0.5198 - learning_rate:
5.0000e-04
Epoch 5/60
438/438 ━━━━━━━━━━━━━━━━━━━━ 482s 1s/step - accuracy: 0.9245 - loss:
0.3579 - val_accuracy: 0.8279 - val_loss: 0.6523 - learning_rate:
5.0000e-04
Epoch 6/60
438/438 ━━━━━━━━━━━━━━━━━━━━ 446s 1s/step - accuracy: 0.9497 - loss:
0.2601 - val_accuracy: 0.8451 - val_loss: 0.5979 - learning_rate:
2.5000e-04
Epoch 7/60
438/438 ━━━━━━━━━━━━━━━━━━━━ 511s 1s/step - accuracy: 0.9483 - loss:
0.2739 - val_accuracy: 0.8305 - val_loss: 0.6349 - learning_rate:
2.5000e-04
137/137 ━━━━━━━━━━━━━━━━━━━━ 39s 276ms/step
RNN Accuracy Score -> 80.49%
              precision    recall  f1-score   support

           0       0.82      0.85      0.84      1988
           1       0.75      0.84      0.80      1437
           2       0.88      0.65      0.75       948

    accuracy                           0.80      4373
   macro avg       0.82      0.78      0.79      4373
weighted avg       0.81      0.80      0.80      4373
```




```
# Doğruluk skorunu hesapla
accuracy = accuracy_score(np.argmax(y_test_onehot, axis=1),
predictions_rnn)
print(f"LSTM Accuracy Score -> {accuracy * 100:.2f}%")
```

```
LSTM Accuracy Score -> 80.49%
```

```
#CNN

import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Conv1D, MaxPooling1D,
Flatten, Dense, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import accuracy_score, classification_report
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split

# Hiperparametreler
max_features = 7000  # Maksimum kelime sayısı
max_len = 100  # Maksimum dizi uzunluğu
embedding_dim = 128  # Gömme boyutu
filter_size = 64  # Konvolüsyonel filtre sayısı
kernel_size = 3  # Konvolüsyonel çekirdek boyutu
pool_size = 2  # Maksimum havuzlama boyutu
dropout_rate = 0.4  # Dropout oranı
```

```
# Veri setinizi hazırlayın (X ve y)
# X_train, X_test ve y_train, y_test veri setlerinin doğru şekilde
tanımlandığından emin olun
# Örnek: X_train = ['metin1', 'metin2', ...], y_train = [-1, 0,
1, ...]

# Tokenizer tanımla ve veriyi dönüştür
tokenizer = Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(X_train)  # X_train metin verisi

# Eğitim ve test verilerini tam sayılara çevir ve sıfırlarla doldur
X_train_seq = tokenizer.texts_to_sequences(X_train)
X_test_seq = tokenizer.texts_to_sequences(X_test)
X_train_pad = pad_sequences(X_train_seq, maxlen=max_len)
X_test_pad = pad_sequences(X_test_seq, maxlen=max_len)

# One-hot encoding ile etiketleri dönüştür
y_train_onehot = to_categorical(y_train, num_classes=3)
y_test_onehot = to_categorical(y_test, num_classes=3)

# Sınıf ağırlıklarını belirleyin (dengesiz sınıflar için)
class_weights = {-1: 1., 0: 2., 1: 3.}

# CNN modelini oluştur
model = Sequential([
    Embedding(max_features, embedding_dim, input_length=max_len,
trainable=True),

    # Konvolüsyonel katmanlar
    Conv1D(filters=filter_size, kernel_size=kernel_size,
activation='relu', padding='same'),
    MaxPooling1D(pool_size=pool_size),

    # İkinci konvolüsyonel katman
    Conv1D(filters=filter_size*2, kernel_size=kernel_size,
activation='relu', padding='same'),
    MaxPooling1D(pool_size=pool_size),

    # Flatten ve tam bağlı katmanlar
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(dropout_rate),  # Dropout katmanı
    BatchNormalization(),  # BatchNormalization ekleyin
    Dense(3, activation='softmax')  # Softmax aktivasyon ile çoklu
sınıf çıkışı
])

# Öğrenme oranını ayarlayın
optimizer = Adam(learning_rate=0.001)
```

```python
# Modeli derle
model.compile(optimizer=optimizer, loss='categorical_crossentropy',
metrics=['accuracy'])

# Erken durdurma ile eğitimi durdurma
early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

# Modeli eğit
model.fit(
    X_train_pad, y_train_onehot,  # y_train_onehot çoklu sınıf
etiketlerinin one-hot kodlanmış hali
    epochs=50, batch_size=32,
    validation_split=0.2,
    class_weight=class_weights,  # Sınıf ağırlıklarını ekle
    callbacks=[early_stopping]
)

# Test verileri üzerinde tahmin yap
predictions_cnn = np.argmax(model.predict(X_test_pad), axis=1)  #
Çoklu sınıf tahmini

# Doğruluk skorunu hesapla
accuracy = accuracy_score(np.argmax(y_test_onehot, axis=1),
predictions_cnn)
print(f"CNN Accuracy Score -> {accuracy * 100:.2f}%")

# Detaylı metrik raporu
print(classification_report(np.argmax(y_test_onehot, axis=1),
predictions_cnn))
```

```
Epoch 1/50
383/383 ━━━━━━━━━━━━━━━━━━━━ 27s 51ms/step - accuracy: 0.5414 - loss:
1.7846 - val_accuracy: 0.7631 - val_loss: 0.6134
Epoch 2/50
383/383 ━━━━━━━━━━━━━━━━━━━━ 18s 47ms/step - accuracy: 0.8836 - loss:
0.5767 - val_accuracy: 0.8399 - val_loss: 0.5088
Epoch 3/50
383/383 ━━━━━━━━━━━━━━━━━━━━ 19s 50ms/step - accuracy: 0.9583 - loss:
0.2257 - val_accuracy: 0.8465 - val_loss: 0.6081
Epoch 4/50
383/383 ━━━━━━━━━━━━━━━━━━━━ 19s 46ms/step - accuracy: 0.9767 - loss:
0.1257 - val_accuracy: 0.8419 - val_loss: 0.6909
Epoch 5/50
383/383 ━━━━━━━━━━━━━━━━━━━━ 20s 46ms/step - accuracy: 0.9836 - loss:
0.0909 - val_accuracy: 0.8363 - val_loss: 0.8703
Epoch 6/50
383/383 ━━━━━━━━━━━━━━━━━━━━ 21s 47ms/step - accuracy: 0.9838 - loss:
0.0878 - val_accuracy: 0.8432 - val_loss: 0.7994
Epoch 7/50
```

```
383/383 ━━━━━━━━━━━━━━━━━━━━ 20s 46ms/step - accuracy: 0.9901 - loss:
0.0611 - val_accuracy: 0.8334 - val_loss: 0.8884
205/205 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step
CNN Accuracy Score -> 82.18%
              precision    recall  f1-score   support

           0       0.83      0.87      0.85      2982
           1       0.83      0.80      0.82      2155
           2       0.79      0.75      0.77      1422

    accuracy                           0.82      6559
   macro avg       0.82      0.81      0.81      6559
weighted avg       0.82      0.82      0.82      6559


#ÇİFT YÖNLÜ LSTM MODELİ

import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Bidirectional, LSTM,
Dense, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import StratifiedKFold
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt

# Hiperparametreler
max_features = 8000  # Maksimum kelime sayısı 8000
max_len = 100        # Maksimum dizi uzunluğu
embedding_dim = 128  # Gömme boyutu
lstm_units = 128     # LSTM birim sayısı
dropout_rate = 0.45   # Dropout oranı 0.45 yapıldı

# Tokenizer tanımla ve veriyi dönüştür
tokenizer = Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(X_train)  # X_train metinleri

X_train_seq = tokenizer.texts_to_sequences(X_train)
X_test_seq = tokenizer.texts_to_sequences(X_test)

X_train_pad = pad_sequences(X_train_seq, maxlen=max_len)
X_test_pad = pad_sequences(X_test_seq, maxlen=max_len)

# One-hot encoding ile etiketleri dönüştür
y_train_onehot = to_categorical(y_train, num_classes=3)
```

```
y_test_onehot = to_categorical(y_test, num_classes=3)

# Sınıf ağırlıklarını belirleyin (dengesiz sınıflar için)
class_weights = {-1: 1., 0: 2., 1: 3.}

# Çapraz doğrulama kurulumu
kfold = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
cv_accuracies = []
cv_losses = []

for train_idx, val_idx in kfold.split(X_train_pad, y_train):
    X_train_cv, X_val_cv = X_train_pad[train_idx],
X_train_pad[val_idx]
    y_train_cv, y_val_cv = y_train_onehot[train_idx],
y_train_onehot[val_idx]

    # Çift Yönlü LSTM modelini oluştur
    model = Sequential([
        Embedding(max_features, embedding_dim, input_length=max_len,
trainable=True),
        Bidirectional(LSTM(lstm_units, return_sequences=False)),
        Dropout(dropout_rate),
        BatchNormalization(),
        Dense(128, activation='relu'),
        Dropout(dropout_rate),
        Dense(3, activation='softmax')
    ])

    # Öğrenme oranını ayarlayın
    optimizer = Adam(learning_rate=0.001)

    # Modeli derle
    model.compile(optimizer=optimizer,
loss='categorical_crossentropy', metrics=['accuracy'])

    # Erken durdurma ile eğitimi durdurma
    early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

    # Modeli eğit
    history = model.fit(
        X_train_cv, y_train_cv,
        epochs=50,
        batch_size=32,
        validation_data=(X_val_cv, y_val_cv),
        class_weight=class_weights,
        callbacks=[early_stopping]
    )

    cv_accuracies.append(max(history.history['val_accuracy']))
```

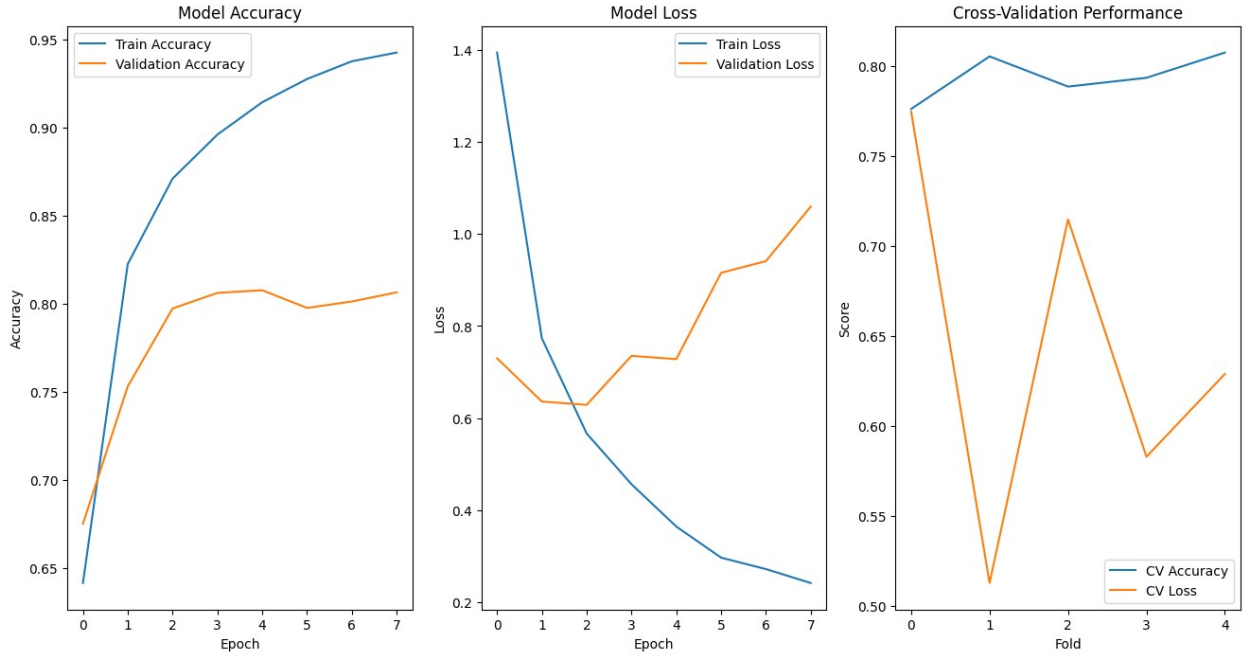
```
    cv_losses.append(min(history.history['val_loss']))

# Test verileri üzerinde tahmin yap
predictions_rnn = np.argmax(model.predict(X_test_pad), axis=1)

# Doğruluk skorunu hesapla
accuracy = accuracy_score(np.argmax(y_test_onehot, axis=1),
predictions_rnn)
print(f"Bidirectional LSTM Accuracy Score -> {accuracy * 100:.2f}%")

# Detaylı metrik raporu
print(classification_report(np.argmax(y_test_onehot, axis=1),
predictions_rnn))

# Eğitim ve doğrulama eğrilerini çiz
plt.figure(figsize=(16, 8))

# Doğruluk eğrisi
plt.subplot(1, 3, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Kayıp eğrisi
plt.subplot(1, 3, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Çapraz doğrulama doğruluğu
plt.subplot(1, 3, 3)
plt.plot(cv_accuracies, label='CV Accuracy')
plt.plot(cv_losses, label='CV Loss')
plt.title('Cross-Validation Performance')
plt.xlabel('Fold')
plt.ylabel('Score')
plt.legend()

plt.show()
```

```
Epoch 1/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 210s 366ms/step - accuracy: 0.5554 -
loss: 1.6650 - val_accuracy: 0.7451 - val_loss: 0.7747
Epoch 2/50
```

```
410/410 ━━━━━━━━━━━━━━━━━━━━ 200s 363ms/step - accuracy: 0.8275 -
loss: 0.7480 - val_accuracy: 0.7213 - val_loss: 0.8683
Epoch 3/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 149s 364ms/step - accuracy: 0.8662 -
loss: 0.5421 - val_accuracy: 0.7558 - val_loss: 0.8124
Epoch 4/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 201s 363ms/step - accuracy: 0.8960 -
loss: 0.4504 - val_accuracy: 0.7692 - val_loss: 0.8612
Epoch 5/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 154s 375ms/step - accuracy: 0.9228 -
loss: 0.3602 - val_accuracy: 0.7762 - val_loss: 0.8613
Epoch 6/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 200s 369ms/step - accuracy: 0.9326 -
loss: 0.2771 - val_accuracy: 0.7753 - val_loss: 0.9185
Epoch 1/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 153s 363ms/step - accuracy: 0.5602 -
loss: 1.6857 - val_accuracy: 0.7243 - val_loss: 0.7453
Epoch 2/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 152s 372ms/step - accuracy: 0.8338 -
loss: 0.7255 - val_accuracy: 0.7951 - val_loss: 0.5127
Epoch 3/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 201s 369ms/step - accuracy: 0.8822 -
loss: 0.5371 - val_accuracy: 0.7841 - val_loss: 0.6304
Epoch 4/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 150s 367ms/step - accuracy: 0.9015 -
loss: 0.4251 - val_accuracy: 0.8054 - val_loss: 0.6300
Epoch 5/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 202s 367ms/step - accuracy: 0.9198 -
loss: 0.3342 - val_accuracy: 0.7908 - val_loss: 0.8398
Epoch 6/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 203s 370ms/step - accuracy: 0.9307 -
loss: 0.3043 - val_accuracy: 0.7850 - val_loss: 0.9758
Epoch 7/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 200s 365ms/step - accuracy: 0.9396 -
loss: 0.2506 - val_accuracy: 0.7944 - val_loss: 0.8618
Epoch 1/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 153s 362ms/step - accuracy: 0.5469 -
loss: 1.7015 - val_accuracy: 0.6859 - val_loss: 0.7189
Epoch 2/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 204s 366ms/step - accuracy: 0.8213 -
loss: 0.7583 - val_accuracy: 0.7560 - val_loss: 0.7148
Epoch 3/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 201s 364ms/step - accuracy: 0.8709 -
loss: 0.5530 - val_accuracy: 0.7252 - val_loss: 0.8515
Epoch 4/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 201s 363ms/step - accuracy: 0.9006 -
loss: 0.4204 - val_accuracy: 0.7777 - val_loss: 0.7206
Epoch 5/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 202s 364ms/step - accuracy: 0.9133 -
```

```
loss: 0.3542 - val_accuracy: 0.7688 - val_loss: 0.8948
Epoch 6/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 202s 363ms/step - accuracy: 0.9283 -
loss: 0.2922 - val_accuracy: 0.7887 - val_loss: 0.9697
Epoch 7/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 201s 361ms/step - accuracy: 0.9451 -
loss: 0.2404 - val_accuracy: 0.7758 - val_loss: 0.9721
Epoch 1/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 151s 357ms/step - accuracy: 0.5495 -
loss: 1.7009 - val_accuracy: 0.7786 - val_loss: 0.6848
Epoch 2/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 147s 359ms/step - accuracy: 0.8387 -
loss: 0.7166 - val_accuracy: 0.7792 - val_loss: 0.5837
Epoch 3/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 145s 354ms/step - accuracy: 0.8745 -
loss: 0.5423 - val_accuracy: 0.7917 - val_loss: 0.5829
Epoch 4/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 204s 359ms/step - accuracy: 0.8990 -
loss: 0.4499 - val_accuracy: 0.7890 - val_loss: 0.6632
Epoch 5/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 203s 362ms/step - accuracy: 0.9199 -
loss: 0.3442 - val_accuracy: 0.7935 - val_loss: 0.7442
Epoch 6/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 198s 353ms/step - accuracy: 0.9327 -
loss: 0.2823 - val_accuracy: 0.7758 - val_loss: 0.9781
Epoch 7/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 201s 351ms/step - accuracy: 0.9355 -
loss: 0.2574 - val_accuracy: 0.7505 - val_loss: 1.1466
Epoch 8/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 204s 356ms/step - accuracy: 0.9525 -
loss: 0.2008 - val_accuracy: 0.7804 - val_loss: 1.0406
Epoch 1/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 152s 360ms/step - accuracy: 0.5453 -
loss: 1.7168 - val_accuracy: 0.6749 - val_loss: 0.7302
Epoch 2/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 144s 349ms/step - accuracy: 0.8261 -
loss: 0.7647 - val_accuracy: 0.7530 - val_loss: 0.6360
Epoch 3/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 205s 357ms/step - accuracy: 0.8738 -
loss: 0.5412 - val_accuracy: 0.7972 - val_loss: 0.6289
Epoch 4/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 142s 346ms/step - accuracy: 0.9051 -
loss: 0.4222 - val_accuracy: 0.8060 - val_loss: 0.7353
Epoch 5/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 146s 356ms/step - accuracy: 0.9225 -
loss: 0.3195 - val_accuracy: 0.8076 - val_loss: 0.7282
Epoch 6/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 198s 346ms/step - accuracy: 0.9357 -
loss: 0.2632 - val_accuracy: 0.7975 - val_loss: 0.9157
```

```
Epoch 7/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 145s 354ms/step - accuracy: 0.9426 -
loss: 0.2563 - val_accuracy: 0.8012 - val_loss: 0.9410
Epoch 8/50
410/410 ━━━━━━━━━━━━━━━━━━━━ 202s 353ms/step - accuracy: 0.9451 -
loss: 0.2309 - val_accuracy: 0.8063 - val_loss: 1.0595
171/171 ━━━━━━━━━━━━━━━━━━━━ 19s 109ms/step
Bidirectional LSTM Accuracy Score -> 78.41%
              precision    recall  f1-score   support

           0       0.73      0.73      0.73      1185
           1       0.78      0.89      0.83      2485
           2       0.83      0.67      0.75      1796

    accuracy                           0.78      5466
   macro avg       0.78      0.76      0.77      5466
weighted avg       0.79      0.78      0.78      5466
```




```python
from gensim.models import Word2Vec

ukuran_vektor = 100

# Assuming 'X_train' contains your preprocessed text data
# Tokenize each document in X_train
tokenized_documents = [doc.split() for doc in X_train]

# Now you can use tokenized_documents in Word2Vec
word2vec_model = Word2Vec(sentences=tokenized_documents,
```

```
                          min_count=1, vector_size=ukuran_vektor,
sg=1)

print(word2vec_model)
```

```
Word2Vec<vocab=16647, vector_size=100, alpha=0.025>
```

```
all_words =word2vec_model.wv.index_to_key
print("50 kata pertama dalam model Word2Vec:")
for index, word in enumerate(all_words):
    if index < 50:
        print(f"{word} : {index}")
    else:
        break
```

```
50 kata pertama dalam model Word2Vec:
eur : 0
net : 1
company : 2
profit : 3
rs : 4
mn : 5
stocks : 6
year : 7
sales : 8
million : 9
shares : 10
finnish : 11
said : 12
crore : 13
co : 14
market : 15
https : 16
quarter : 17
group : 18
new : 19
mln : 20
operating : 21
per : 22
bank : 23
stock : 24
period : 25
finland : 26
share : 27
business : 28
loss : 29
india : 30
5 : 31
000 : 32
first : 33
```

```
services : 34
euro : 35
may : 36
financial : 37
markets : 38
oyj : 39
3 : 40
nifty : 41
1 : 42
also : 43
4 : 44
cent : 45
high : 46
2 : 47
capital : 48
oil : 49
```

```
# Assuming 'df' is your original DataFrame that contains the 'text'
column
train_df = df.copy()  # Create a copy of the original DataFrame and
name it 'train_df'
train_df['Text_prepro'] = train_df['text'].apply(preprocess_text)  #
Apply preprocessing function
max_length = train_df['Text_prepro'].apply(lambda x:
len(x.split())).max() # Now calculate max_length
```

```
max_length
```

```
60
```

```
max_length_index = train_df['Text_prepro'].apply(len).idxmax()
print("Index baris dengan max_length adalah :", max_length_index)
```

```
Index baris dengan max_length adalah : 10959
```

```
train_df.at[max_length_index, 'Text_prepro']
```

```
{"type":"string"}
```

```
# Replace 'Text' with the actual column name containing the original
text
train_df.at[max_length_index, 'text']  # Assuming 'text' is the
correct column name
```

```
{"type":"string"}
```

```
sequences = []
for doc in train_df['Text_prepro']:
    text = clean_text(doc)
    sequence = []
    for word in text:
```

```
        try:
            # Attempt to get the index of the word from the Word2Vec
model
            sequence.append(word2vec_model.wv.key_to_index[word])
        except KeyError:
            # If the word is not found, either ignore it or assign a
default value
            # Option 1: Ignore the unknown word
            # pass
            # Option 2: Assign a default value (e.g., 0)
            sequence.append(0)
    sequences.append(sequence)

len(sequences)
```

```
21862
```

```
from keras.preprocessing.sequence import pad_sequences
padded_sequences = pad_sequences(sequences, maxlen=max_length,
padding='post')

padded_sequences.shape
```

```
(21862, 60)
```

```
y = np.asarray(train_df['score'])

jumlah_kelas=len(train_df["score"].unique())

jumlah_kelas
```

```
3
```

```
from sklearn.model_selection import train_test_split
X_train, X_val, y_train, y_val = train_test_split(padded_sequences, y,
                                                  test_size=0.3,
                                                  random_state=42,
stratify=y)

embedding_matrix = np.zeros((len(word2vec_model.wv.key_to_index) + 1,
word2vec_model.vector_size))
for word, i in word2vec_model.wv.key_to_index.items():
    embedding_vector = word2vec_model.wv[word]
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector

from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout,
Input,Embedding,GlobalMaxPooling1D
model = Sequential()
model.add(Input(shape=(max_length,)))
model.add(Embedding(input_dim=embedding_matrix.shape[0],
```

```
output_dim=embedding_matrix.shape[1],
                    trainable=False))
model.add(LSTM(ukuran_vektor, return_sequences=True))
model.add(GlobalMaxPooling1D())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(jumlah_kelas, activation='softmax'))

from keras.optimizers import Adam
optimizer = Adam(learning_rate=0.0001)
model.compile(optimizer=optimizer,
loss='sparse_categorical_crossentropy', metrics=['accuracy'])

from keras.callbacks import EarlyStopping
early_stopping = EarlyStopping(monitor='val_loss', patience=15,
restore_best_weights=True)

#BIDIRECTIONAL LSTM ENBEDDING TEKNIGI

import numpy as np
import pandas as pd
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout,
BatchNormalization, Bidirectional
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split

# Data preparation (example)
# Assuming you have your data in a DataFrame 'train_df' with
'Text_prepro' and 'score' columns
X = train_df['Text_prepro']  # Select text column
y = train_df['score']  # Select score/label column

# 1. Etiketleri sıfırdan başlayacak şekilde dönüştürme
y = y.astype('category').cat.codes  # Convert labels to 0, 1, 2 (if
they were -1, 0, 1 originally)
print(np.unique(y))  # Kontrol et: 0, 1, 2 olmalı

# 2. Eğitim ve doğrulama setlerini ayırma
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,
random_state=42, stratify=y)

# 3. Verileri tokenizasyon ve sıralama (X_train ve X_val'ı uygun
formatta hazırlama)
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

max_features = 7000  # Max kelime sayısı
max_len = 100  # Maksimum dizi uzunluğu
tokenizer = Tokenizer(num_words=max_features)
```

```
tokenizer.fit_on_texts(X_train)  # Metinleri eğitiyoruz

X_train_seq = tokenizer.texts_to_sequences(X_train)  # Eğitim verisini
sayılara çevir
X_val_seq = tokenizer.texts_to_sequences(X_val)  # Doğrulama verisini
sayılara çevir
X_train_pad = pad_sequences(X_train_seq, maxlen=max_len)  # Sıfırlama
ile padding yapıyoruz
X_val_pad = pad_sequences(X_val_seq, maxlen=max_len)  # Aynı şekilde
doğrulama verisini sıfırlıyoruz

# 4. Modeli oluşturma
model = Sequential([
    Embedding(input_dim=max_features, output_dim=128,
input_length=max_len, trainable=True),
    Bidirectional(LSTM(128, activation='relu',
kernel_initializer='he_normal', return_sequences=True)),
    LSTM(64, activation='relu', kernel_initializer='he_normal'),
    BatchNormalization(),
    Dropout(0.4),
    Dense(3, activation='softmax')  # 3 sınıf için softmax aktivasyonu
])

# Modeli derleme
model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# 5. Erken durdurma için callback
early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

# 6. Modeli eğitme
history = model.fit(
    X_train_pad, y_train,  # Eğitim verisi
    epochs=60,  # Epoch sayısını artırdık
    batch_size=256,  # Batch boyutunu biraz artırdık
    validation_data=(X_val_pad, y_val),  # Doğrulama verisi
    callbacks=[early_stopping]  # Erken durdurma
)

# 7. Modeli değerlendirme
predictions = np.argmax(model.predict(X_val_pad), axis=1)  # Tahmin
yapma

# 8. Sınıflandırma raporunu yazdırma
print(classification_report(y_val, predictions, target_names=['-1',
'0', '1']))

[0 1 2]
Epoch 1/60
```

```
69/69 ━━━━━━━━━━━━━━━━━━━━ 142s 2s/step - accuracy: 0.6049 - loss:
0.8558 - val_accuracy: 0.5573 - val_loss: 0.9744
Epoch 2/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 147s 2s/step - accuracy: 0.8651 - loss:
0.3727 - val_accuracy: 0.5609 - val_loss: 0.9129
Epoch 3/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 128s 2s/step - accuracy: 0.9122 - loss:
0.2522 - val_accuracy: 0.6261 - val_loss: 0.8166
Epoch 4/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 149s 2s/step - accuracy: 0.9298 - loss:
0.2010 - val_accuracy: 0.7265 - val_loss: 0.6899
Epoch 5/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 128s 2s/step - accuracy: 0.9445 - loss:
0.1606 - val_accuracy: 0.7837 - val_loss: 0.5685
Epoch 6/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 144s 2s/step - accuracy: 0.9543 - loss:
0.1275 - val_accuracy: 0.8027 - val_loss: 0.5217
Epoch 7/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 140s 2s/step - accuracy: 0.9670 - loss:
0.0977 - val_accuracy: 0.8168 - val_loss: 0.5561
Epoch 8/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 131s 2s/step - accuracy: 0.9694 - loss:
0.0880 - val_accuracy: 0.8177 - val_loss: 0.6502
Epoch 9/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 141s 2s/step - accuracy: 0.9755 - loss:
0.0713 - val_accuracy: 0.8075 - val_loss: 0.7751
Epoch 10/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 139s 2s/step - accuracy: 0.9808 - loss:
0.0547 - val_accuracy: 0.8141 - val_loss: 0.9346
Epoch 11/60
69/69 ━━━━━━━━━━━━━━━━━━━━ 145s 2s/step - accuracy: 0.9844 - loss:
0.0487 - val_accuracy: 0.8091 - val_loss: 0.9917
137/137 ━━━━━━━━━━━━━━━━━━━━ 21s 153ms/step
              precision    recall  f1-score   support

          -1       0.87      0.62      0.72       948
           0       0.78      0.91      0.84      1988
           1       0.81      0.77      0.79      1437

    accuracy                           0.80      4373
   macro avg       0.82      0.77      0.78      4373
weighted avg       0.81      0.80      0.80      4373


# Replace the original evaluate line:
# loss, accuracy = model.evaluate(X_val, y_val, verbose=0)
# with:
loss, accuracy = model.evaluate(X_val_pad, y_val, verbose=0)
# Use X_val_pad which is the preprocessed and padded version of your
```

```
text data
print(f'Test Accuracy: {accuracy*100:.2f}%')
```

```
Test Accuracy: 80.27%
```

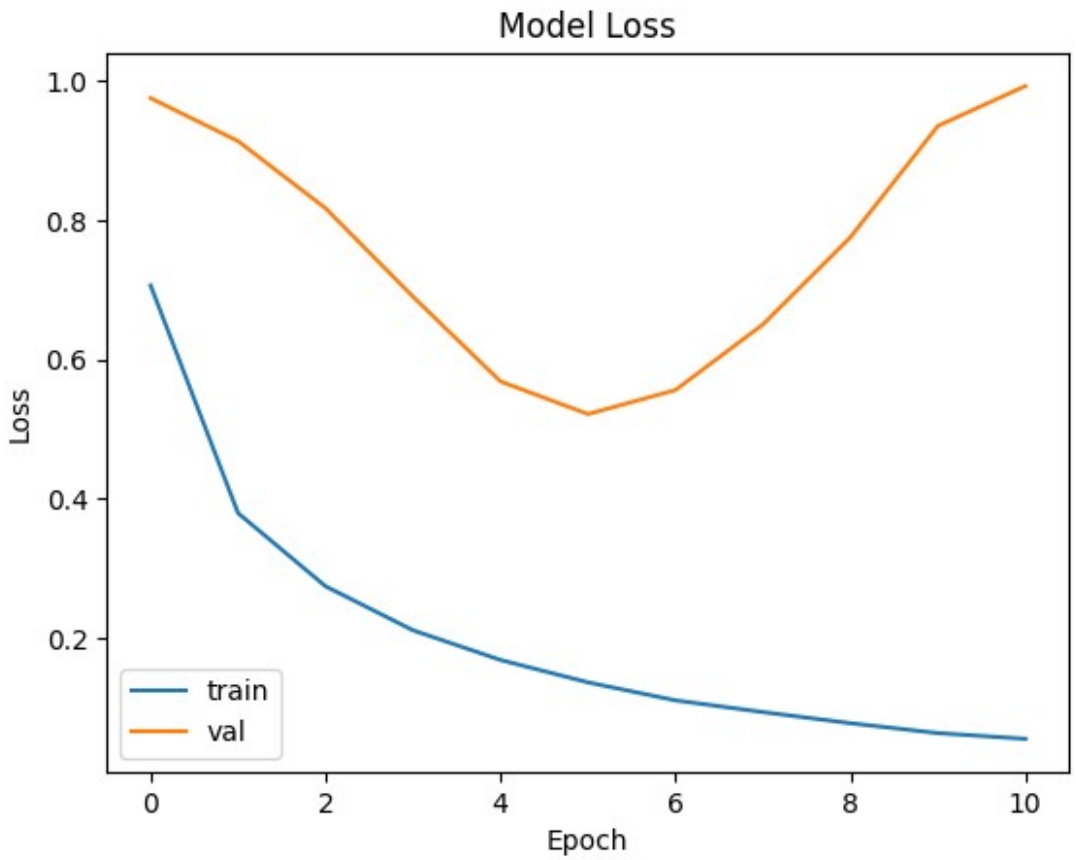
```
print("Konfigurasi Lapisan Embedding:")
print(model.layers[0].get_config())
```

```
Konfigurasi Lapisan Embedding:
{'name': 'embedding_9', 'trainable': True, 'dtype': {'module':
'keras', 'class_name': 'DTypePolicy', 'config': {'name': 'float32'},
'registered_name': None}, 'input_dim': 7000, 'output_dim': 128,
'embeddings_initializer': {'module': 'keras.initializers',
'class_name': 'RandomUniform', 'config': {'minval': -0.05, 'maxval':
0.05, 'seed': None}, 'registered_name': None},
'embeddings_regularizer': None, 'activity_regularizer': None,
'embeddings_constraint': None, 'mask_zero': False}
```

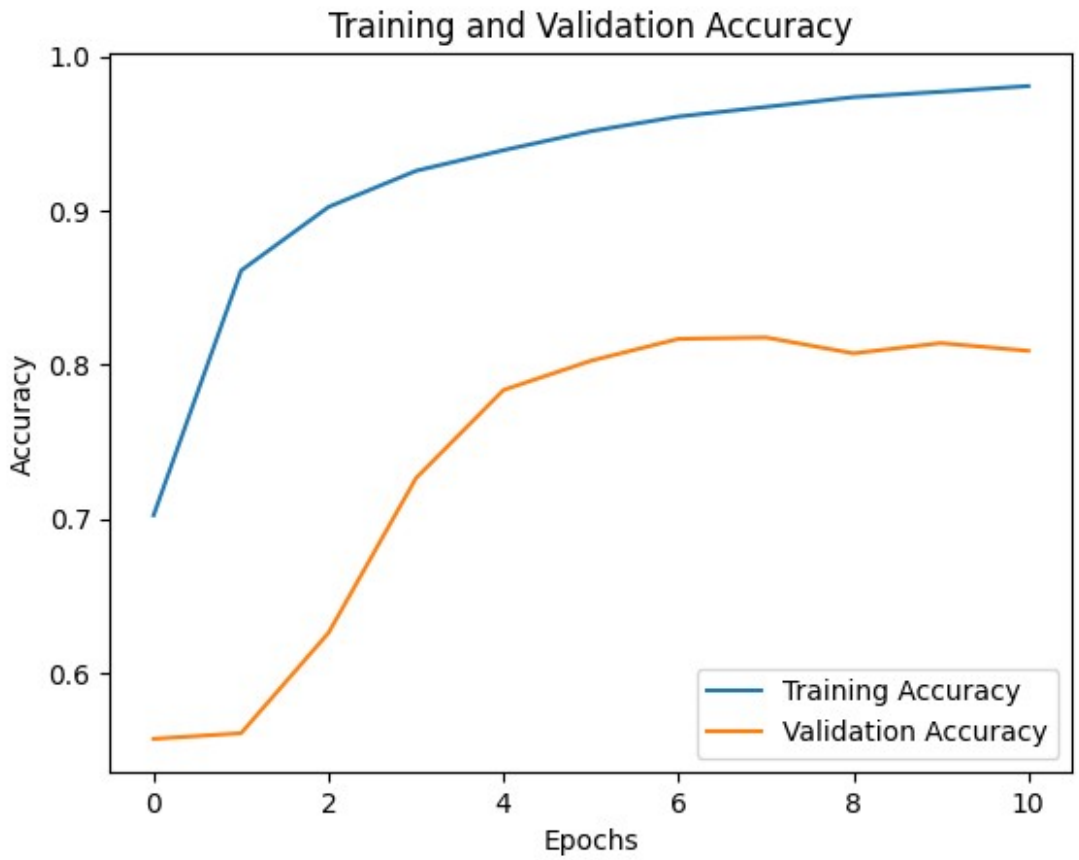
```
print("Bobot Lapisan Embedding:")
print(model.layers[0].get_weights()[0])
```

```
Bobot Lapisan Embedding:
[[-0.01774926 -0.003418   -0.01801335 ...  0.00724279 -0.03029587
  -0.03292952]
 [-0.04101794 -0.00211915  0.00365264 ... -0.01733536  0.02789244
   0.03499065]
 [-0.06540317 -0.04706103  0.04208628 ... -0.02002771  0.02027632
  -0.02619204]
 ...
 [-0.04424844  0.05441351  0.04604282 ... -0.02619411  0.05062838
  -0.00964622]
 [ 0.04119474  0.00778585 -0.06094953 ... -0.03502693  0.03397828
   0.01464775]
 [ 0.00865341  0.01557361 -0.04098716 ... -0.01287615 -0.02880764
  -0.06647932]]
```

```
import matplotlib.pyplot as plt
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='val')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```




```
accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']
plt.plot(accuracy, label='Training Accuracy')
plt.plot(val_accuracy, label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



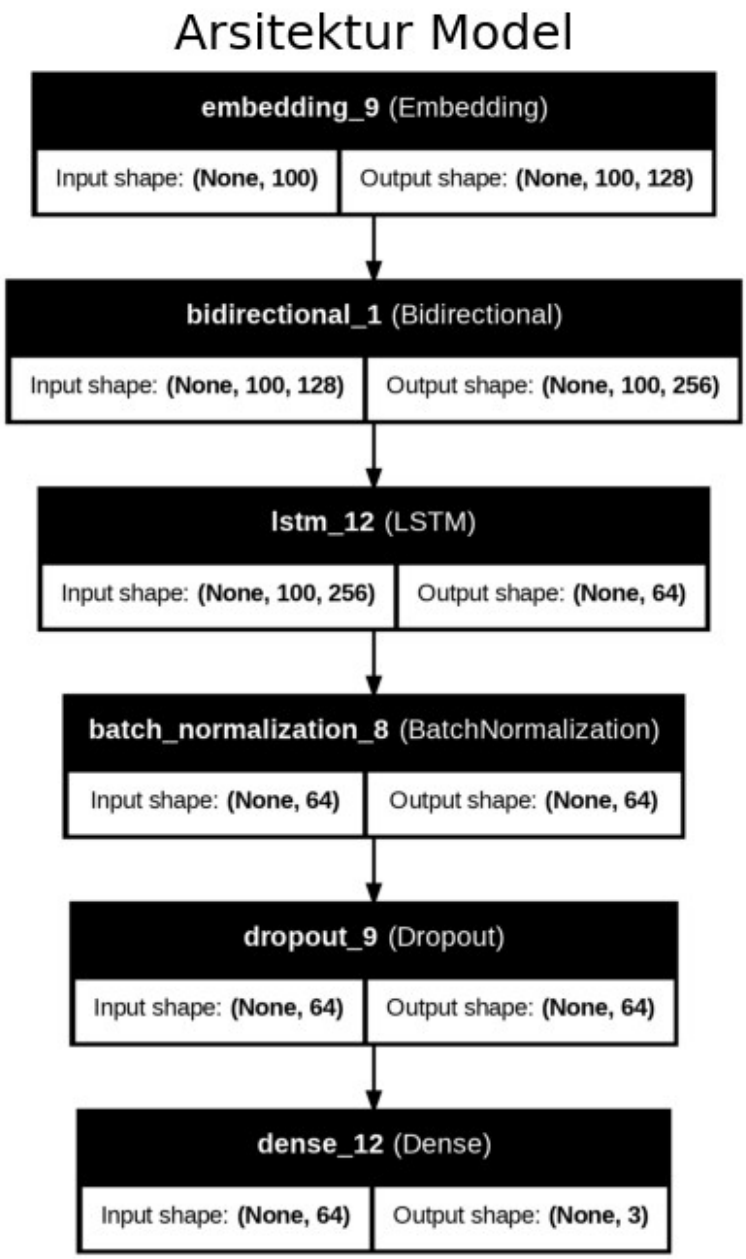

```
model.summary()
```

```
Model: "sequential_9"
```

```
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃         Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━┩
│ embedding_9 (Embedding)              │ (None, 100, 128)            │         896,000 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ bidirectional_1 (Bidirectional)      │ (None, 100, 256)            │         263,168 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ lstm_12 (LSTM)                       │ (None, 64)                  │          82,176 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ batch_normalization_8                │ (None, 64)                  │
```

```
256 │
│ (BatchNormalization)                │                             │
│
├─────────────────────────────────────┼─────────────────────────────┼
──────────────────┤
│ dropout_9 (Dropout)                 │ (None, 64)                  │
0 │
├─────────────────────────────────────┼─────────────────────────────┼
──────────────────┤
│ dense_12 (Dense)                    │ (None, 3)                   │
195 │
└─────────────────────────────────────┴─────────────────────────────┴
──────────────────┘

 Total params: 3,725,131 (14.21 MB)

 Trainable params: 1,241,667 (4.74 MB)

 Non-trainable params: 128 (512.00 B)

 Optimizer params: 2,483,336 (9.47 MB)
```

```python
from keras.utils import plot_model
file_name = 'arsitektur_model.png'
plot_model(model, to_file=file_name, show_shapes=True,
show_layer_names=True)
plt.figure(figsize=(8,8))
img = plt.imread(file_name)
plt.imshow(img)
plt.title('Arsitektur Model', fontsize=18)
plt.axis('off')
plt.savefig(file_name)
plt.show()
```

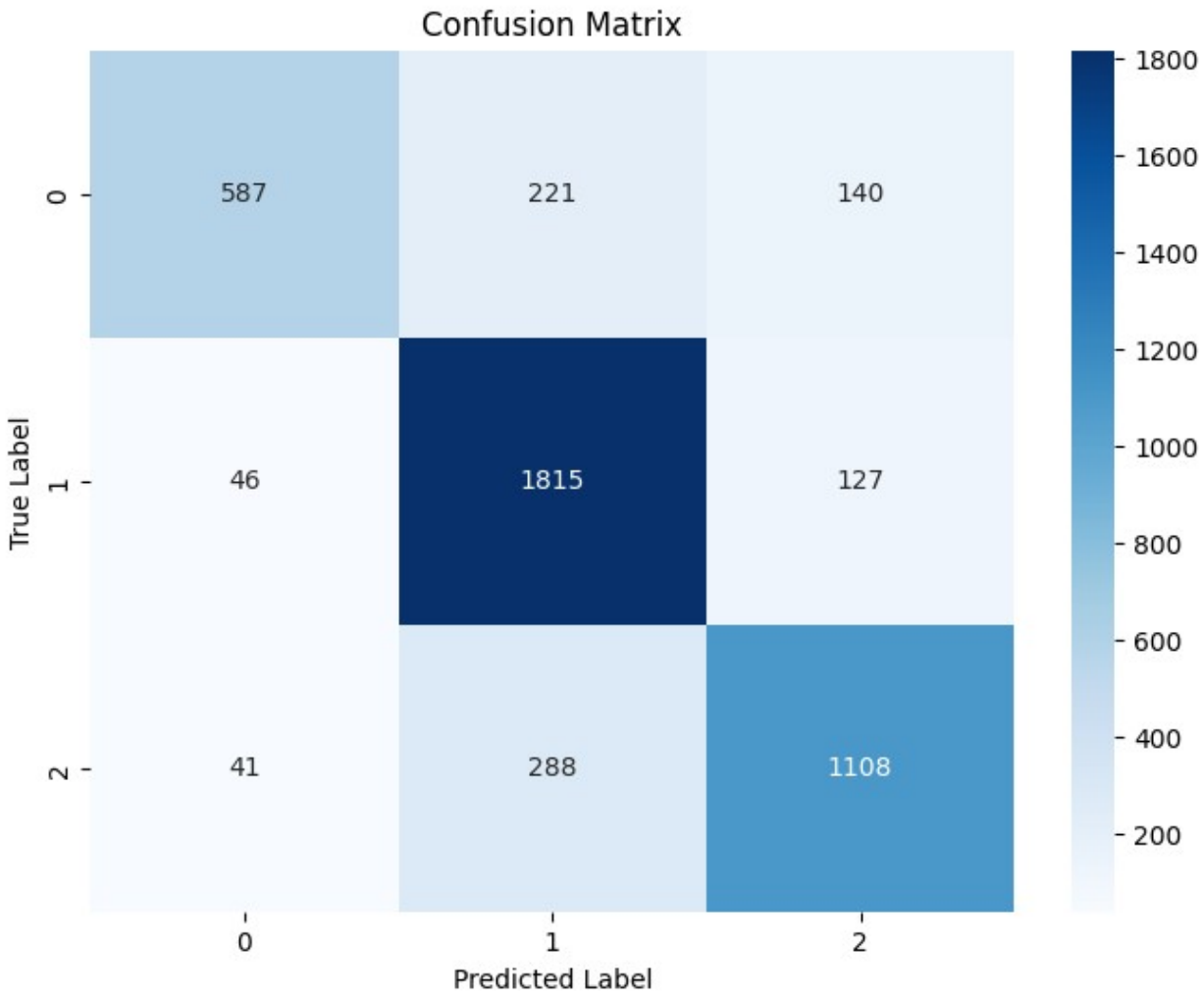



```
from sklearn.metrics import classification_report
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Assuming X_val contains raw text strings and tokenizer is defined:
X_val_seq = tokenizer.texts_to_sequences(X_val)  # Convert to
sequences
X_val_pad = pad_sequences(X_val_seq, maxlen=max_length)  # Pad
sequences

y_pred = model.predict(X_val_pad)  # Predict on padded sequences
y_pred_classes = np.argmax(y_pred, axis=1)
```

```
report = classification_report(y_val, y_pred_classes)
print("Classification Report:")
print(report)
```

```
137/137 ━━━━━━━━━━━━━━━━━━━━ 17s 117ms/step
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.62      0.72       948
           1       0.78      0.91      0.84      1988
           2       0.81      0.77      0.79      1437

    accuracy                           0.80      4373
   macro avg       0.82      0.77      0.78      4373
weighted avg       0.81      0.80      0.80      4373
```

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
cm = confusion_matrix(y_val, y_pred_classes)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```




```
model.save("model_Amazon_Product_Reviews.h5")
word2vec_model.save("word2vec_model.model")
train_df.to_csv("train_data.csv", index=False)
```

```
WARNING:absl:You are saving your model as an HDF5 file via
`model.save()` or `keras.saving.save_model(model)`. This file format
is considered legacy. We recommend using instead the native Keras
format, e.g. `model.save('my_model.keras')` or
`keras.saving.save_model(model, 'my_model.keras')`.
```