In [1]:
```
import kagglehub
crowdflower_twitter_airline_sentiment_path = kagglehub.dataset_download('crowd

print('Data source import complete.')
```

```
Downloading from https://www.kaggle.com/api/v1/datasets/download/crowdflower/tw
itter-airline-sentiment?dataset_version_number=4...
100%|██████████| 2.55M/2.55M [00:00<00:00, 31.8MB/s]
Extracting files...
Data source import complete.
```

KÜTÜPHANELERİN YÜKLENMESİ

In [2]:
```
# Basic Operation
import pandas as pd
import numpy as np

# Text Preprocessing & Cleaning
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.corpus import stopwords
import re


from sklearn.model_selection import train_test_split # Split Data
from imblearn.over_sampling import SMOTE # Handling Imbalanced

# Model Building
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import MultinomialNB
from xgboost import XGBClassifier
from sklearn.svm import SVC


from sklearn.metrics import classification_report , confusion_matrix , accurac


# Data Visualization
import matplotlib.pyplot as plt
from wordcloud import WordCloud
from termcolor import cprint
import seaborn as sns
import warnings


warnings.filterwarnings('ignore')
%matplotlib inline

import os
```

```
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

VERİSETİNİN YÜKLENMESİ

In [3]:
```
import os
import pandas as pd
import kagglehub
crowdflower_twitter_airline_sentiment_path = kagglehub.dataset_download('crowd

print('Data source import complete.')

# Construct the full path to the Tweets.csv file using the downloaded dataset
tweets_csv_path = os.path.join(crowdflower_twitter_airline_sentiment_path, 'Tw

# Load The Data using the correct path
df = pd.read_csv(tweets_csv_path)
```

```
Data source import complete.
```

VERİSETİYLE İLGİLİ KONTROLLER. İLK SATIRLAR VE KUYRUK KONTROL EDİLİYOR

In [ ]:
```
```

In [4]:
```
df.head()
```

Out[4]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativ
0	570306133677760513	neutral	1.0000	
1	570301130888122368	positive	0.3486	
2	570301083672813571	neutral	0.6837	
3	570301031407624196	negative	1.0000	B
4	570300817074462722	negative	1.0000	

In [5]:
```
df.tail()
```

Out[5]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	neg
14635	569587686496825344	positive	0.3487	
14636	569587371693355008	negative	1.0000	
14637	569587242672398336	neutral	1.0000	
14638	569587188687634433	negative	1.0000	
14639	569587140490866689	neutral	0.6771	

EDA KISMI

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Data columns (total 15 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   tweet_id                      14640 non-null  int64  
 1   airline_sentiment             14640 non-null  object 
 2   airline_sentiment_confidence  14640 non-null  float64
 3   negativereason                9178 non-null   object 
 4   negativereason_confidence     10522 non-null  float64
 5   airline                       14640 non-null  object 
 6   airline_sentiment_gold        40 non-null     object 
 7   name                          14640 non-null  object 
 8   negativereason_gold           32 non-null     object 
 9   retweet_count                 14640 non-null  int64  
 10  text                          14640 non-null  object 
 11  tweet_coord                   1019 non-null   object 
 12  tweet_created                 14640 non-null  object 
 13  tweet_location                9907 non-null   object 
 14  user_timezone                 9820 non-null   object 
dtypes: float64(2), int64(2), object(11)
memory usage: 1.7+ MB
```

In [7]:
```
df.describe()
```

Out[7]:

	tweet_id	airline_sentiment_confidence	negativereason_confidence	r
count	1.464000e+04	14640.000000	10522.000000	
mean	5.692184e+17	0.900169	0.638298	
std	7.791112e+14	0.162830	0.330440	
min	5.675883e+17	0.335000	0.000000	
25%	5.685592e+17	0.692300	0.360600	
50%	5.694779e+17	1.000000	0.670600	
75%	5.698905e+17	1.000000	1.000000	
max	5.703106e+17	1.000000	1.000000	

In [8]:
```
df.shape
```

Out[8]: (14640, 15)

NNAN DEĞER KONTROLÜ

In [9]:
```
df.isnull().sum()
```

Out[9]:

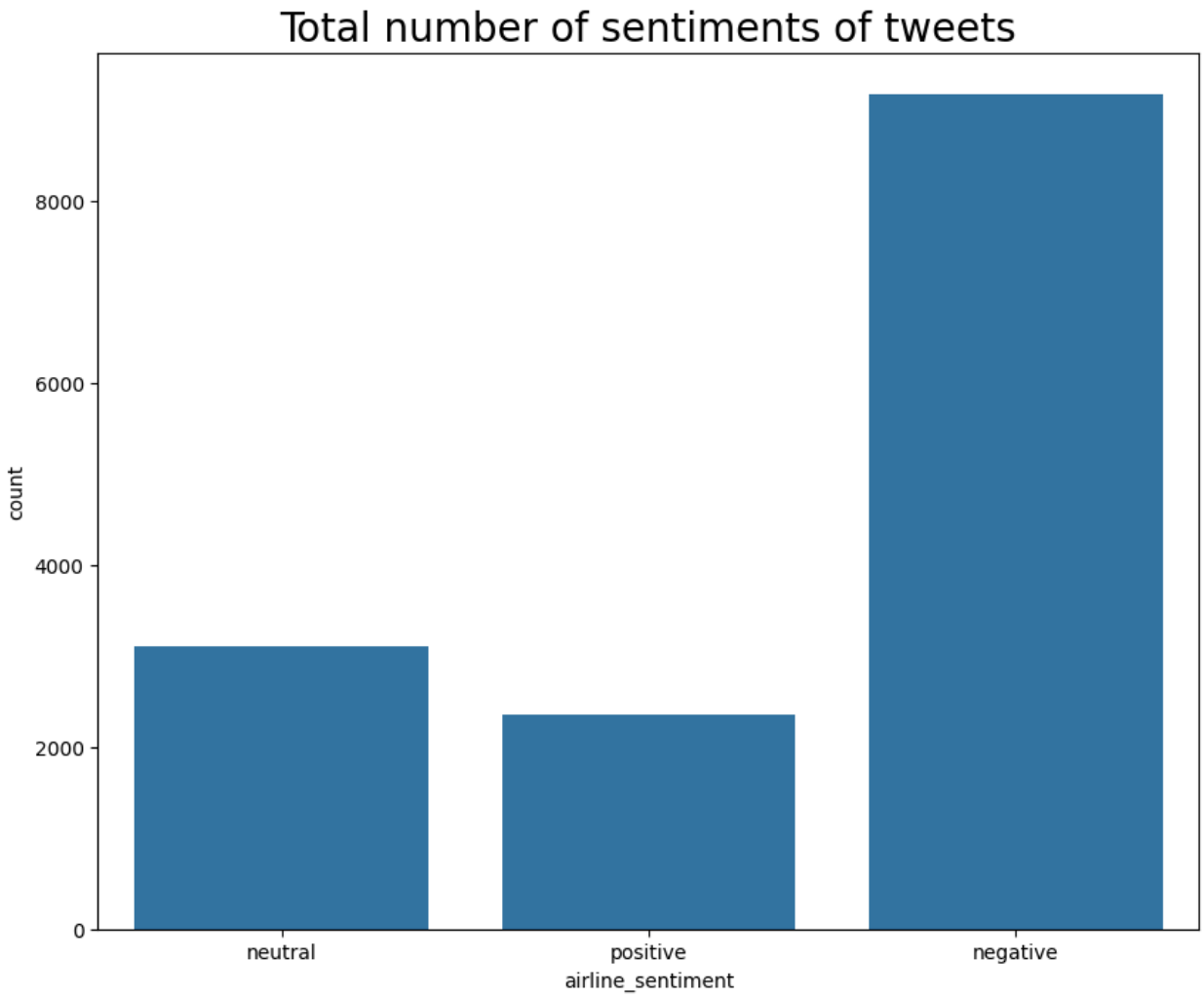
	0
tweet_id	0
airline_sentiment	0
airline_sentiment_confidence	0
negativereason	5462
negativereason_confidence	4118
airline	0
airline_sentiment_gold	14600
name	0
negativereason_gold	14608
retweet_count	0
text	0
tweet_coord	13621
tweet_created	0
tweet_location	4733
user_timezone	4820

dtype: int64

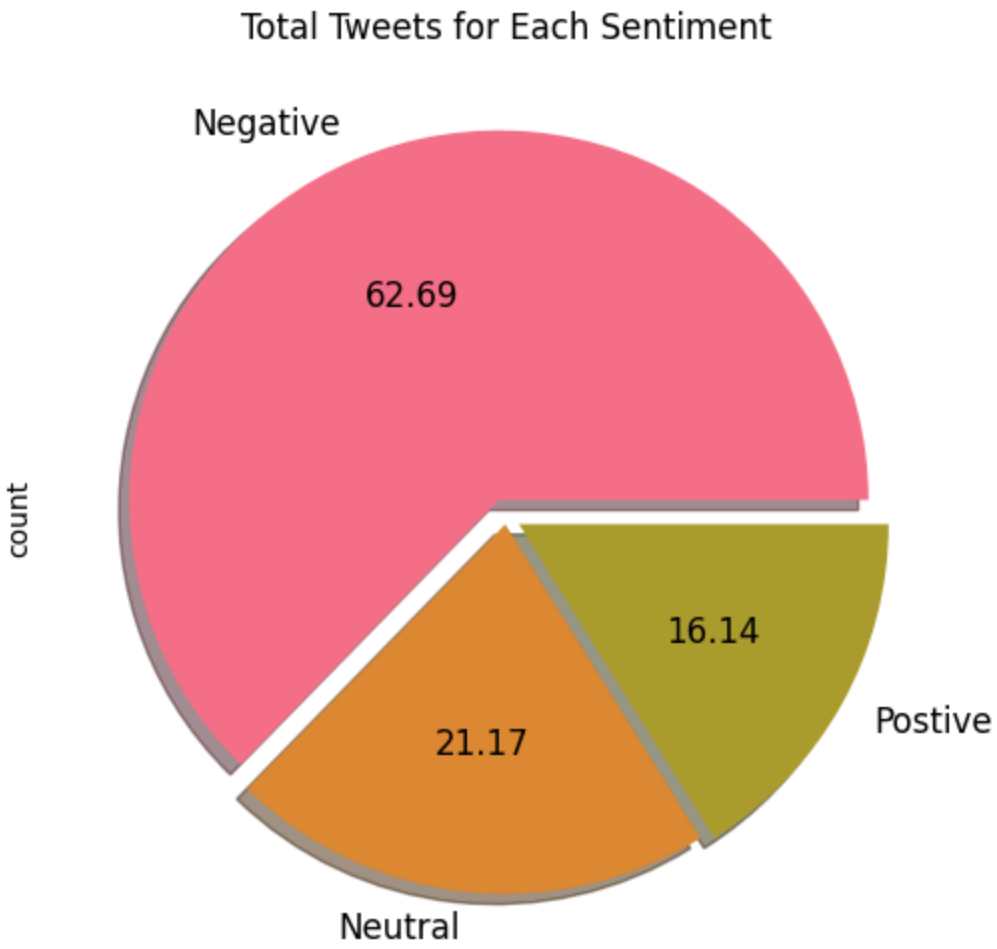
DATA VISUALIZATION

In [10]:
```
cprint("Total number of sentiments of tweets :",'green')
print(df.airline_sentiment.value_counts())
plt.figure(figsize = (10, 8))
ax = sns.countplot(x = 'airline_sentiment', data = df)
ax.set_title(label = 'Total number of sentiments of tweets', fontsize = 20)
plt.show()
```

```
Total number of sentiments of tweets :
airline_sentiment
negative    9178
neutral     3099
positive    2363
Name: count, dtype: int64
```

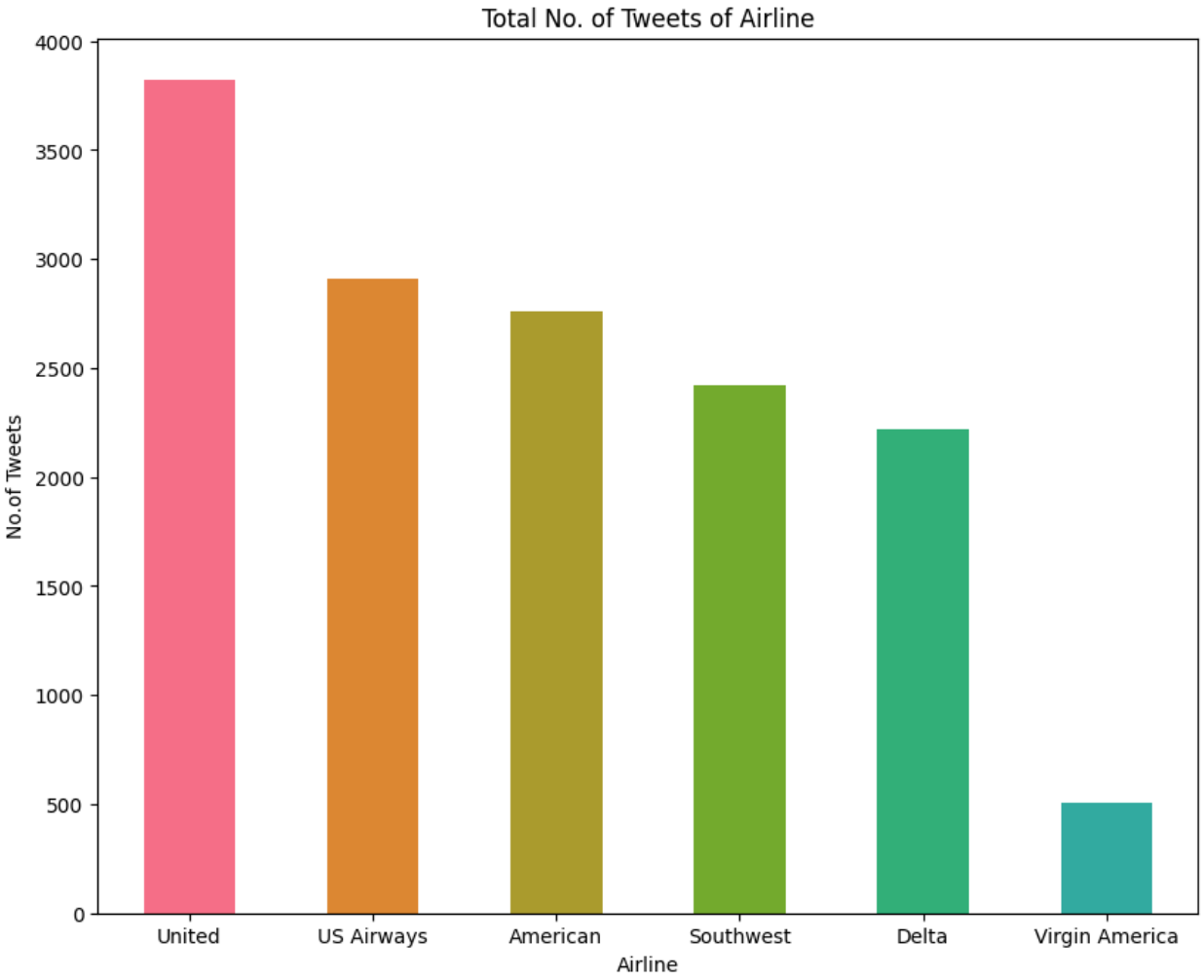


In [11]:
```
ax.set_title(label = 'Total number of sentiments of tweets:')
colors=sns.color_palette('husl',10)
pd.Series(df['airline_sentiment']).value_counts().plot(kind='pie',colors=color

plt.show()
```



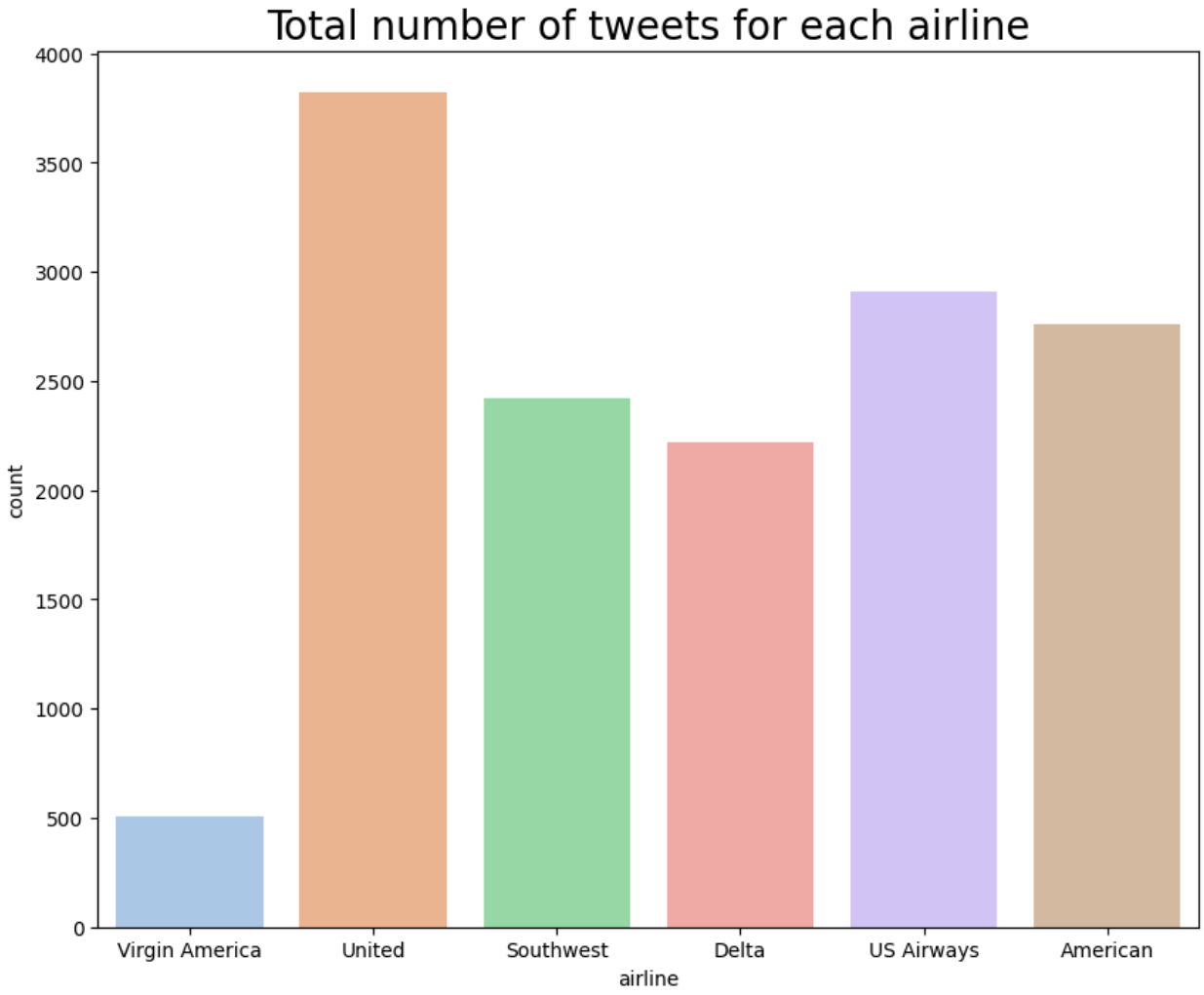
In [12]:
```
colors=sns.color_palette('husl',10)
pd.Series(df['airline']).value_counts().plot(kind="bar",color=colors,figsize=(
plt.xlabel('Airline',fontsize=10)
plt.ylabel('No.of Tweets',fontsize=10)
```

Out[12]:
```
Text(0, 0.5, 'No.of Tweets')
```



In [13]:
```
cprint("Total number of tweets for each airline :",'green')
print(df.groupby('airline')['airline_sentiment'].count())

plt.figure(figsize = (10, 8))
ax = sns.countplot(x = 'airline', data = df, palette = 'pastel')
ax.set_title(label = 'Total number of tweets for each airline', fontsize = 20)
plt.show()

cprint("Total number of sentiment tweets for each airline :",'green')
airlines= ['US Airways','United','American','Southwest','Delta','Virgin Americ
for i in airlines :
    print('{} : \n'.format(i),df.loc[df.airline == i].airline_sentiment.value_
```

```
Total number of tweets for each airline :
airline
American          2759
Delta             2222
Southwest         2420
US Airways        2913
United            3822
Virgin America     504
Name: airline_sentiment, dtype: int64
```

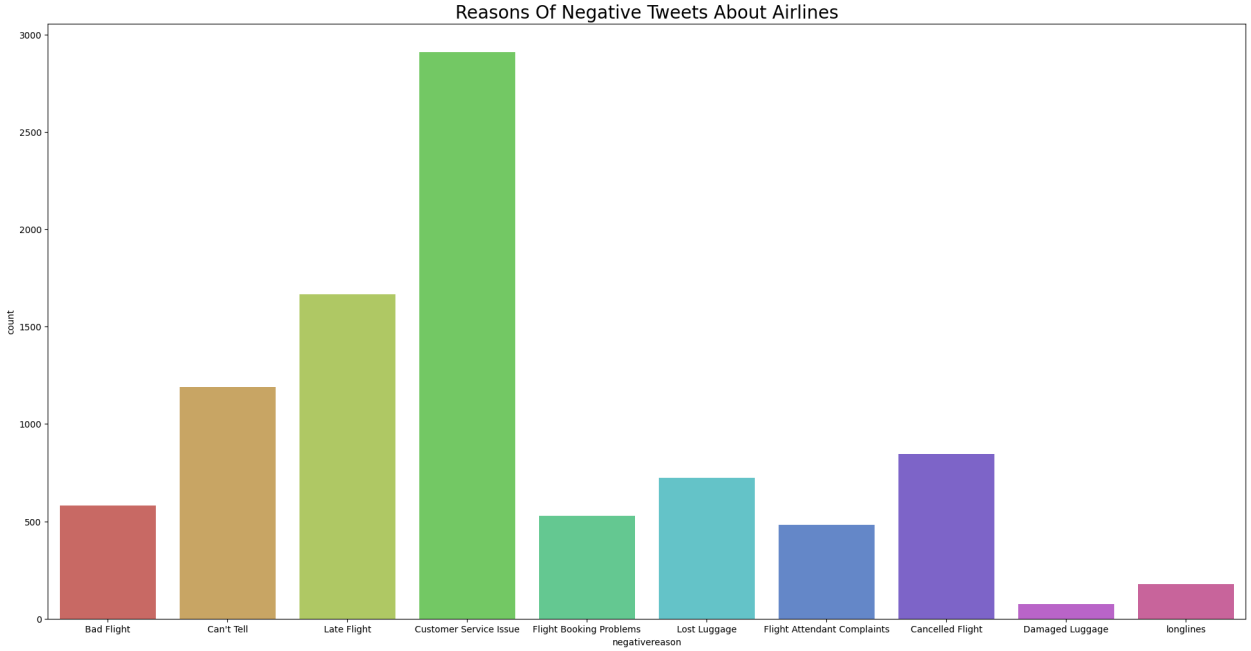

Total number of tweets for each airline
4000
3500
3000
2500
2000
1500
1000
500
0
count
Virgin America
United
Southwest
Delta
US Airways
American
airline

```
Total number of sentiment tweets for each airline :
US Airways :
 airline_sentiment
negative    2263
neutral      381
positive     269
Name: count, dtype: int64
United :
 airline_sentiment
negative    2633
neutral      697
positive     492
Name: count, dtype: int64
American :
 airline_sentiment
negative    1960
neutral      463
positive     336
Name: count, dtype: int64
Southwest :
 airline_sentiment
negative    1186
neutral      664
positive     570
Name: count, dtype: int64
Delta :
 airline_sentiment
negative    955
neutral     723
positive    544
Name: count, dtype: int64
Virgin America :
 airline_sentiment
negative    181
neutral     171
positive    152
Name: count, dtype: int64
```

NEGATİF TWEETLERİN SEBEBİ

In [14]:
```
cprint('Reasons Of Negative Tweets :','green')
print(df.negativereason.value_counts())

plt.figure(figsize = (24, 12))
sns.countplot(x = 'negativereason', data = df, palette = 'hls')
plt.title('Reasons Of Negative Tweets About Airlines', fontsize = 20)
plt.show()
```

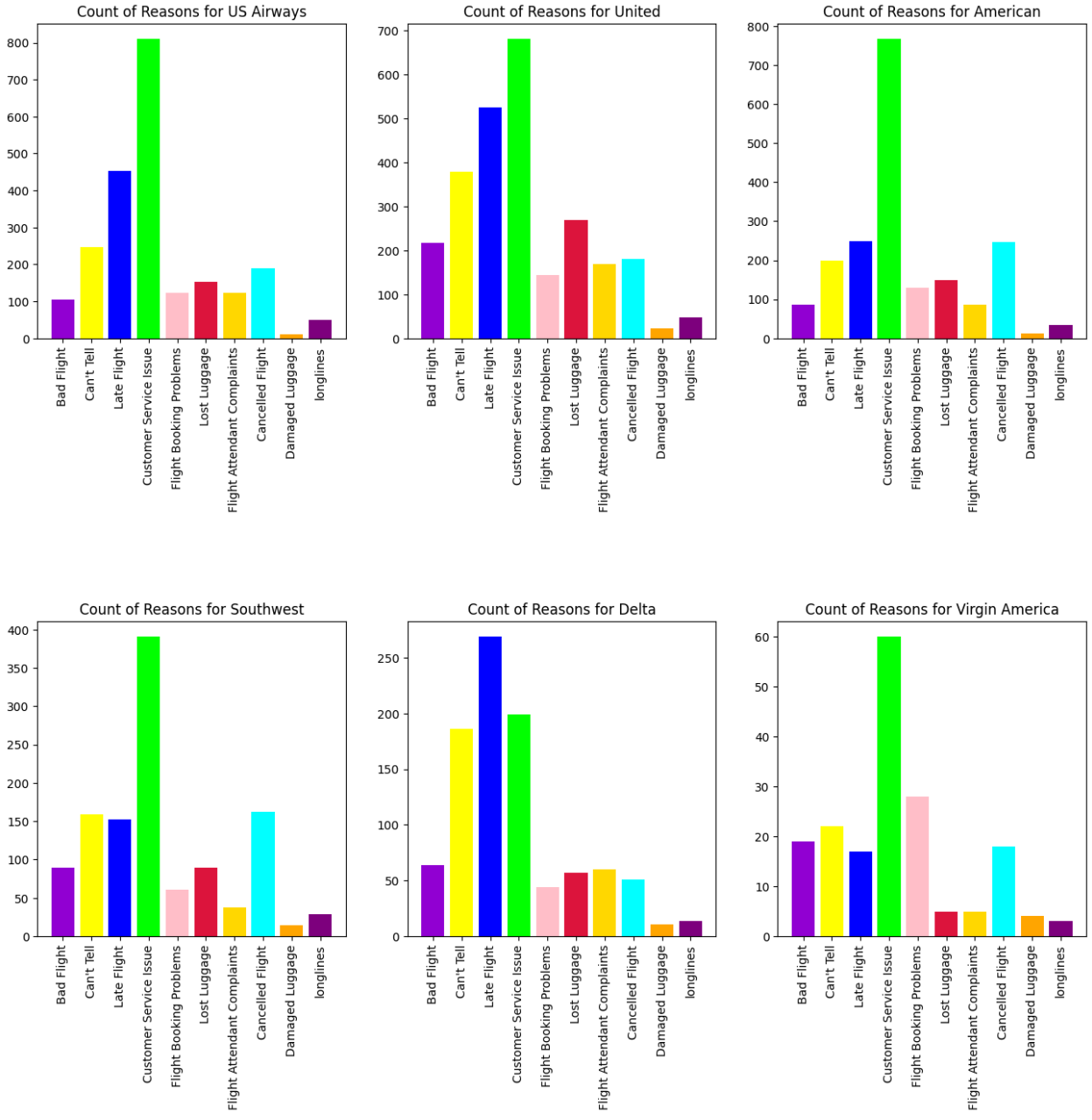
```
Reasons Of Negative Tweets :
negativereason
Customer Service Issue         2910
Late Flight                    1665
Can't Tell                     1190
Cancelled Flight                847
Lost Luggage                    724
Bad Flight                      580
Flight Booking Problems         529
Flight Attendant Complaints     481
longlines                       178
Damaged Luggage                  74
Name: count, dtype: int64
```



NEGATİF TWEETLERİN SEBEBİNİN FİRMALARA GÖRE DAĞILIMI

In [15]:
```
NR_Count=df['negativereason'].value_counts()
def NCount(Airline):
    airlineName =df[df['airline']==Airline]
    count= airlineName['negativereason'].value_counts()
    Unique_reason= df['negativereason'].unique()
    Unique_reason=[x for x in Unique_reason if str(x) != 'nan']
    Reason_frame=pd.DataFrame({'Reasons':Unique_reason})
    Reason_frame['count']=Reason_frame['Reasons'].apply(lambda x: count[x])
    return Reason_frame

def Plot_Reason(airline):
    a= NCount(airline)
    count=a['count']
    Id = range(1,(len(a)+1))
```

```
    plt.bar(Id,count, color=['darkviolet','yellow','blue','lime','pink','crims
    plt.xticks(Id,a['Reasons'],rotation=90)
    plt.title('Count of Reasons for '+ airline)

plt.figure(2,figsize=(16, 14))
for i in airlines:
    indices= airlines.index(i)
    plt.subplot(2,3,indices+1)
    plt.subplots_adjust(hspace=0.9)
    Plot_Reason(i)
```

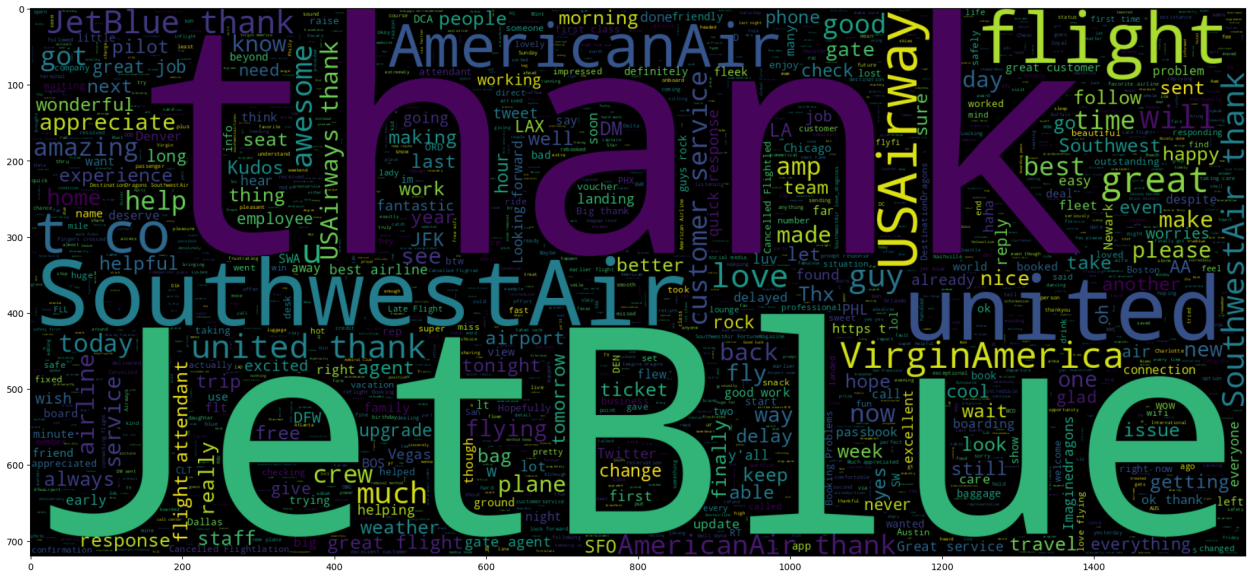


DUYGU KISMININ AYRILMASI /BÖLÜMLENMESİ

In [16]:
```
positive=df[df['airline_sentiment']=='positive'].text
neutral=df[df['airline_sentiment']=='neutral'].text
negative=df[df['airline_sentiment']=='negative'].text
```

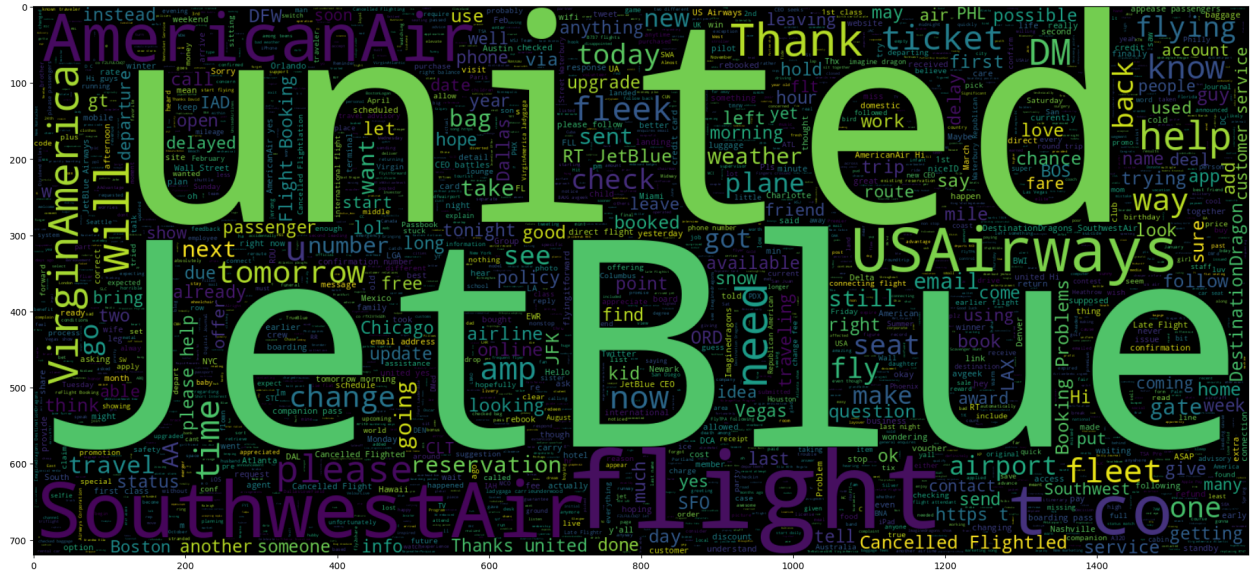
POZİTİF DUYGULARIN WORLDCLOUDU

In [17]:
```
plt.figure(figsize=(24,20))
world_cloud_postive=WordCloud(min_font_size=3,max_words=3200,width=1600,height
plt.imshow(world_cloud_postive,interpolation='bilinear')
ax.grid(False)
```



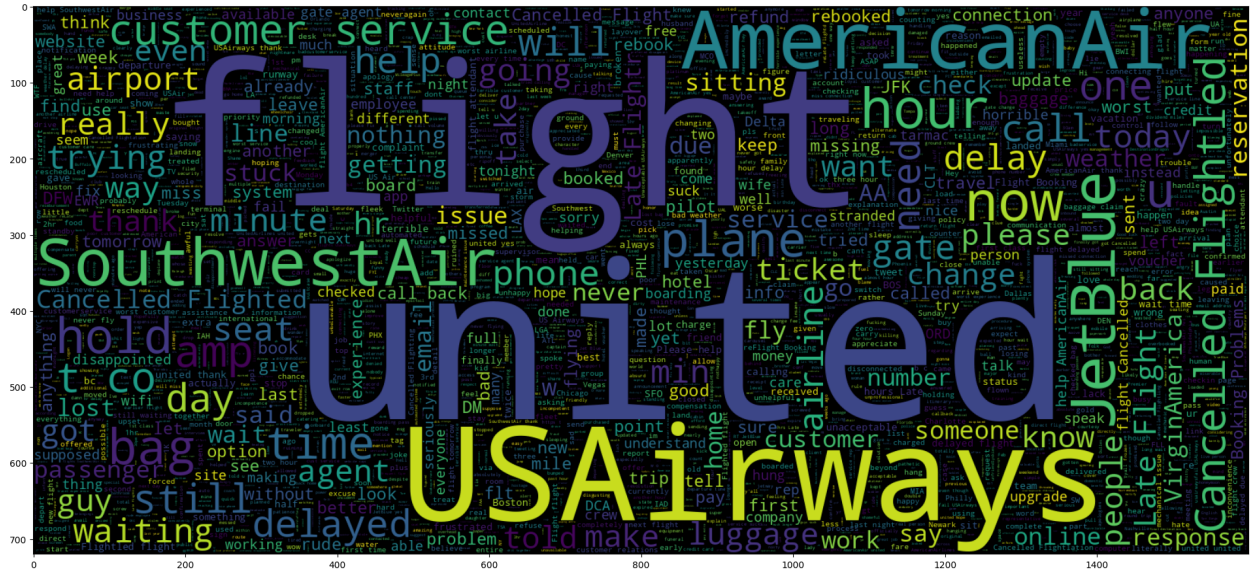
NÖTR DUYGULARIN WORLDCLOUDU

In [18]:
```
plt.figure(figsize=(24,12))
world_cloud_neutral=WordCloud(min_font_size=3,max_words=3200,width=1600,height
plt.imshow(world_cloud_neutral,interpolation='bilinear')
ax.grid(False)
```



NEGATİF DUYGULARIN WORLDCLOUDU

In [19]:
```
plt.figure(figsize = (24,12))
worldcould_neg = WordCloud(min_font_size = 3,  max_words = 3200 , width = 1600
plt.imshow(worldcould_neg,interpolation = 'bilinear')
ax.grid(False)
```



PREPROCESSING

In [20]:
```
# convert Sentiments to 0,1,2
def convert_Sentiment(sentiment):
    if  sentiment == "positive":
        return 2
    elif sentiment == "neutral":
```

```
        return 1
    elif sentiment == "negative":
        return 0
```

In [21]:
```
# Apply convert_Sentiment function
df.airline_sentiment = df.airline_sentiment.apply(lambda x : convert_Sentiment
```

In [22]:
```
df.airline_sentiment
```

Out[22]:

	airline_sentiment
0	1
1	2
2	1
3	0
4	0
...	...
14635	2
14636	0
14637	1
14638	0
14639	1

14640 rows × 1 columns

dtype: int64

In [23]:
```
import nltk
nltk.download('stopwords')
# Remove stop words
def remove_stopwords(text):
    text = ' '.join([word for word in text.split() if word not in (stopwords.w
    return text

# Remove url
def remove_url(text):
    url = re.compile(r'https?://\S+|www\.\S+')
    return url.sub(r'',text)

# Remove punct
def remove_punct(text):
    table = str.maketrans('', '', string.punctuation)
    return text.translate(table)

# Remove html
```

```
def remove_html(text):
    html=re.compile(r'<.*?>')
    return html.sub(r'',text)

# Remove @username
def remove_username(text):
    return re.sub('@[^\s]+','',text)

# Remove emojis
def remove_emoji(text):
    emoji_pattern = re.compile("["
                           u"\U0001F600-\U0001F64F"  # emoticons
                           u"\U0001F300-\U0001F5FF"  # symbols & pictographs
                           u"\U0001F680-\U0001F6FF"  # transport & map symbols
                           u"\U0001F1E0-\U0001F1FF"  # flags (iOS)
                           u"\U00002702-\U000027B0"
                           u"\U000024C2-\U0001F251"
                           "]+", flags=re.UNICODE)
    return emoji_pattern.sub(r'', text)


# Decontraction text
def decontraction(text):
    text = re.sub(r"won\'t", " will not", text)
    text = re.sub(r"won\'t've", " will not have", text)
    text = re.sub(r"can\'t", " can not", text)
    text = re.sub(r"don\'t", " do not", text)

    text = re.sub(r"can\'t've", " can not have", text)
    text = re.sub(r"ma\'am", " madam", text)
    text = re.sub(r"let\'s", " let us", text)
    text = re.sub(r"ain\'t", " am not", text)
    text = re.sub(r"shan\'t", " shall not", text)
    text = re.sub(r"sha\n't", " shall not", text)
    text = re.sub(r"o\'clock", " of the clock", text)
    text = re.sub(r"y\'all", " you all", text)
    text = re.sub(r"n\'t", " not", text)
    text = re.sub(r"n\'t've", " not have", text)
    text = re.sub(r"\'re", " are", text)
    text = re.sub(r"\'s", " is", text)
    text = re.sub(r"\'d", " would", text)
    text = re.sub(r"\'d've", " would have", text)
    text = re.sub(r"\'ll", " will", text)
    text = re.sub(r"\'ll've", " will have", text)
    text = re.sub(r"\'t", " not", text)
    text = re.sub(r"\'ve", " have", text)
    text = re.sub(r"\'m", " am", text)
    text = re.sub(r"\'re", " are", text)
    return text

# Seperate alphanumeric
def seperate_alphanumeric(text):
    words = text
```

```
    words = re.findall(r"[^\W\d_]+|\d+", words)
    return " ".join(words)

def cont_rep_char(text):
    tchr = text.group(0)

    if len(tchr) > 1:
        return tchr[0:2]

def unique_char(rep, text):
    substitute = re.sub(r'(\w)\1+', rep, text)
    return substitute

def char(text):
    substitute = re.sub(r'[^a-zA-Z]',' ',text)
    return substitute

# combaine negative reason with  tweet (if exsist)
df['final_text'] = df['negativereason'].fillna('') + ' ' + df['text']


# Apply functions on tweets
df['final_text'] = df['final_text'].apply(lambda x : remove_username(x))
df['final_text'] = df['final_text'].apply(lambda x : remove_url(x))
df['final_text'] = df['final_text'].apply(lambda x : remove_emoji(x))
df['final_text'] = df['final_text'].apply(lambda x : decontraction(x))
df['final_text'] = df['final_text'].apply(lambda x : seperate_alphanumeric(x))
df['final_text'] = df['final_text'].apply(lambda x : unique_char(cont_rep_char
df['final_text'] = df['final_text'].apply(lambda x : char(x))
df['final_text'] = df['final_text'].apply(lambda x : x.lower())
df['final_text'] = df['final_text'].apply(lambda x : remove_stopwords(x))
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

In [24]:

```
# result
df['final_text']
```

Out[24]:

	final_text
0	said
1	plus added commercials experience tacky
2	today must mean need take another trip
3	bad flight really aggressive blast obnoxious e...
4	ca tell really big bad thing
...	...
14635	thank got different flight chicago
14636	customer service issue leaving minutes late fl...
14637	please bring american airlines blackberry
14638	customer service issue money change flight ans...
14639	ppl need know many seats next flight plz put u...

14640 rows × 1 columns

dtype: object

In [25]:
```
X = df['final_text']
y = df['airline_sentiment']
```

TFIDF

In [26]:
```
tfid = TfidfVectorizer()
X_final =  tfid.fit_transform(X)
```

SINIF DENGESİZLİĞİNİN GİDERİLMESİ

In [26]:
```

```

In [27]:
```
# Handling imbalanced using SMOTE
smote = SMOTE()
x_sm,y_sm = smote.fit_resample(X_final,y)
```

TRAIN TEST AYRIMI %75-%25

In [28]:
```
X_train , X_test , y_train , y_test = train_test_split(x_sm , y_sm , test_size
```

Random Forest

In [29]:
```
random_forest_classifier = RandomForestClassifier()
random_forest_classifier.fit(X_train,y_train)
```

Out[29]:
```
RandomForestClassifier()
```

In [30]:
```
random_forest_classifier_prediction =  random_forest_classifier.predict(X_test
```

Randome Forest Accuracy Score

In [31]:
```
accuracy_score(random_forest_classifier_prediction,y_test)
```

Out[31]:
```
0.9558396281231842
```

XGBClassifier

In [32]:
```
xgb = XGBClassifier()
xgb.fit(X_train,y_train)
```

Out[32]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_roun
ds=None,
              enable_categorical=False, eval_metric=None, feature_typ
es=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_b
in=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
```

In [33]:
```
xgb_prediction =  xgb.predict(X_test)
```

XGBClassifier Accuracy Score

In [34]:
```
accuracy_score(xgb_prediction,y_test)
```

Out[34]: 0.9161824520627542

Gradient Boosting Classifier

In [35]:
```
gbc = GradientBoostingClassifier()
gbc.fit(X_train,y_train)
```

Out[35]:
```
GradientBoostingClassifier()
```

In [36]:
```
gbc_prediction =  gbc.predict(X_test)
```

In [37]:
```
accuracy_score(gbc_prediction,y_test)
```

Out[37]: 0.8765252760023242

SVM

In [38]:
```
svm = SVC()
svm.fit(X_train,y_train)
```

Out[38]:
```
SVC()
```

In [39]:
```
svm_prediction =  svm.predict(X_test)
```

In [40]:
```
accuracy_score(svm_prediction,y_test)
```

Out[40]: 0.9362289366647298

Naive Bayes

In [41]:
```
nb = MultinomialNB()
nb.fit(X_train,y_train)
```

Out[41]:
```
MultinomialNB()
```

In [42]:
```
nb_prediction =  nb.predict(X_test)
```

In [43]:
```
accuracy_score(nb_prediction,y_test)
```

Out[43]:
```
0.8608367228355607
```

Decision Tree

In [44]:
```
des_tree_classifier = DecisionTreeClassifier()
des_tree_classifier.fit(X_train,y_train)
```

Out[44]:
```
DecisionTreeClassifier()
```

In [45]:
```
des_tree_classifier_prediction=des_tree_classifier.predict(X_test)
```

In [46]:
```
accuracy_score(des_tree_classifier_prediction,y_test)
```

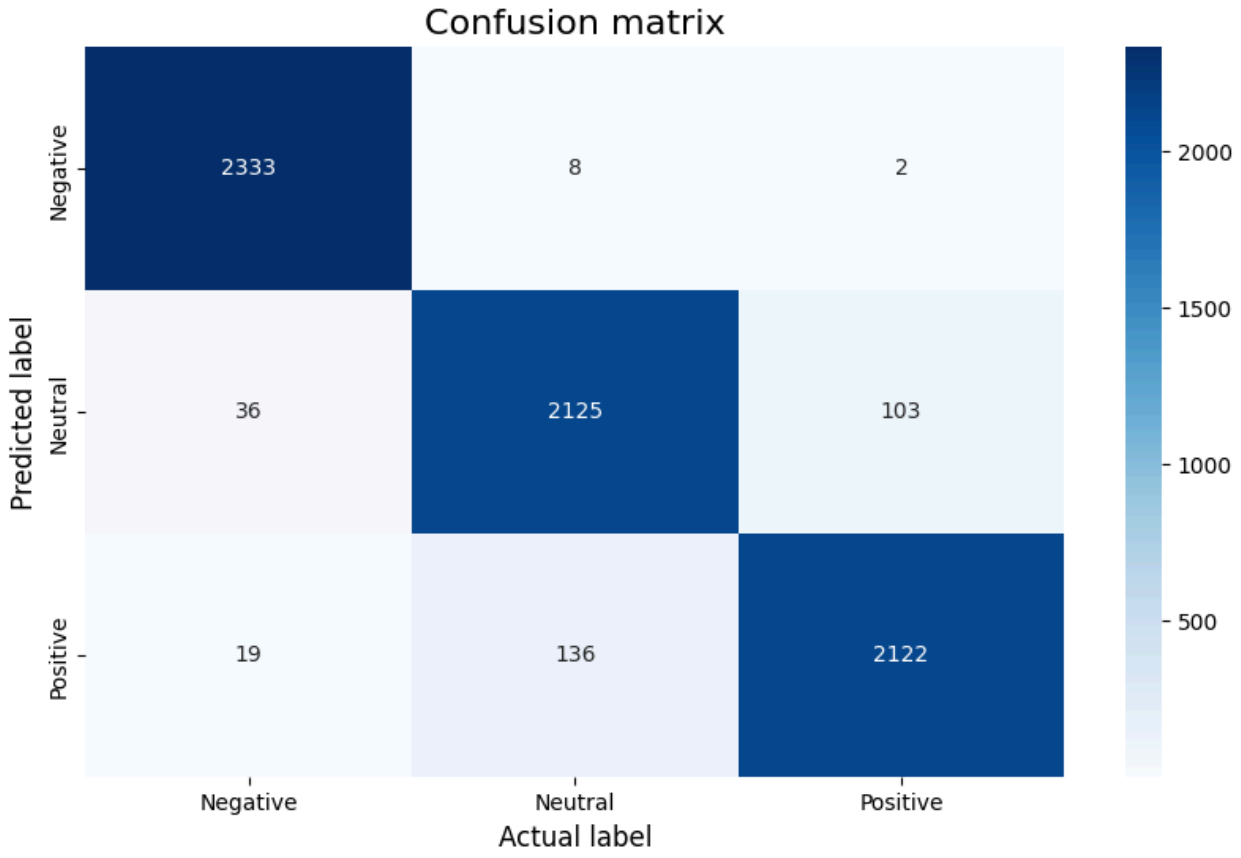
Out[46]:
```
0.9356478791400349
```

MODEL PERFORMANSININ GÖRSELLEŞTİRİLMESİ

In [47]:
```
cr = classification_report(y_test, random_forest_classifier_prediction)
```

In [48]:
```
print("Classification Report:\n----------------------\n", cr)

cm = confusion_matrix(y_test,random_forest_classifier_prediction)


# plot confusion matrix
plt.figure(figsize=(10,6))
sentiment_classes = ['Negative', 'Neutral', 'Positive']
sns.heatmap(cm, cmap=plt.cm.Blues, annot=True, fmt='d',
            xticklabels=sentiment_classes,
            yticklabels=sentiment_classes)
plt.title('Confusion matrix', fontsize=16)
plt.xlabel('Actual label', fontsize=12)
plt.ylabel('Predicted label', fontsize=12)
plt.show()
```

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

           0       0.98      1.00      0.99      2343
           1       0.94      0.94      0.94      2264
           2       0.95      0.93      0.94      2277

    accuracy                           0.96      6884
   macro avg       0.96      0.96      0.96      6884
weighted avg       0.96      0.96      0.96      6884
```



In [ ]: