BrandPulse: Decoding SXSW Sentiment for Competitive Intelligence

Business Understanding:

Problem Statement

Brands invest massive resources in marketing at major events like SXSW, but they lack a real-time, data-driven understanding of public perception. They struggle to answer:

- Is our campaign resonating positively?
- How does sentiment towards our brand compare to our competitors?
- What specific product features or marketing stunts are people talking about (good or bad or neutral)?

Stakeholders

1. Marketing Directors at Tech Companies (e.g., Apple, Google):

- “Do we **double down** on this activation or cut our losses?”
- “Which competitor is heating up **right now**?”
- “What messaging is actually **resonating** with the audience?”

2. Brand Strategy Consultants:

"Need actionable competitive intelligence for client advising."

- “What is our **true position** vs competitors?”
- “What **emerging trends** should we capitalize on?”
- “Where are the **market gaps** we can own?”

3. For a CMO *After SXSW*

- “What should we change for next year?”
- “How should we allocate our **next event budget**?”

Value Proposition

BrandPulse analyzes social media chatter from SXSW to provide quantified brand sentiment and competitive positioning, enabling evidence-based marketing decisions.

Multi-Class Analysis

```
# Libraries
!pip install tensorflow
!pip install imblearn
!pip install keras-tuner
!pip install transformers datasets accelerate torch
import pandas as pd # load, clean, manipulate tables
import numpy as np # fast numerical operations
import matplotlib.pyplot as plt # Basic plotting (bar charts, histograms, etc.)
import seaborn as sns # More advanced, prettier statistical plots.
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_extraction.text import CountVectorizer # Converts text → bag-of-words numeric vectors.
from sklearn.feature_extraction.text import TfidfVectorizer # Converts text → TF-IDF weighted vectors.
from sklearn.model_selection import train_test_split, RandomizedSearchCV, GridSearchCV
                        # GridSearchCV - Tries every possible combination of hyperparameters you provide.
                        # Randomized Search CV - Picks random combinations of hyperparameters.
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix, classification
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC # ML Algorithm to find the best possible boundary to separate classes
```

```
from sklearn.utils import class_weight # Balance classes
from sklearn.naive_bayes import MultinomialNB # Multinomial Naive Bayes - learn word frequencies in each class and pr
from sklearn.neighbors import KNeighborsClassifier # Predicts a label by looking at the k closest data points in the
from sklearn.tree import DecisionTreeClassifier # learns a series of if–else rules that split the data into groups un
from imblearn.over_sampling import SMOTE # fix imbalanced datasets by creating synthetic samples for minority classes
from imblearn.pipeline import make_pipeline, Pipeline # chain multiple steps (preprocessing + modeling) into one sing
import plotly.graph_objects as go # build highly customized, interactive visualizations
import plotly.express as px # Plotly's high-level, fast, simple plotting interface.
from scipy.stats import randint
from tensorflow.keras.preprocessing.text import Tokenizer # converts raw text into smaller units (tokens)
from tensorflow.keras.preprocessing.sequence import pad_sequences # adds zeros (or another value) so all sequences ma
from tensorflow.keras.models import Sequential # Sequential is a model where each layer feeds directly into the next
from tensorflow.keras.layers import Embedding, LSTM, Bidirectional, Dense, Dropout
                      # Embedding - Converts each integer token into a dense vector that represents meaning.
                      # LSTM - (LongShortTermMemory)Learns patterns in sequences — especially order, context, and lon
                      # Bidirectional - Runs LSTM forward and backward over the sentence..
                      # Dense layer - A fully connected layer that makes final predictions.
                      # Dropout - Randomly turns off some neurons during training to prevent overfitting.
from tensorflow.keras.optimizers import Adam, AdamW # used to update neural network weights during training, a smarte
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
                      # EarlyStopping - Stops training automatically when the model stops improving on a validation s
                      # ReduceLROnPlateau - automatically reduces the learning rate when a monitored metric stops imp
from tensorflow.keras.layers import Input # defines the entry point of a neural network
from tensorflow.keras.utils import to_categorical # converts integer class labels into one-hot encoded vectors.
from keras_tuner import RandomSearch
from transformers import DistilBertTokenizerFast
from transformers import DistilBertForSequenceClassification
from transformers import TrainingArguments
from transformers import Trainer

from sklearn.dummy import DummyClassifier # a baseline classifier

import re # Regular expressions for text cleaning (remove URLs, symbols, etc.)
import datasets

import nltk # natural language toolkit
from nltk.corpus import stopwords # Common words
from nltk.tokenize import word_tokenize # splitting text into words or subunits (tokens)
from nltk.stem import PorterStemmer # reducing words to their root form
from nltk.stem import WordNetLemmatizer # reduces words to dictionary/base form
# from nltk.sentiment.vader import SentimentIntensityAnalyzer

nltk.download('stopwords')
nltk.download('punkt') # pre-trained tokenizer model in NLTK
nltk.download('wordnet') # WordNet is a large lexical database of English words.
# nltk.download('vader_lexicon')
nltk.download('punkt_tab') # tokenization of tabular text

import warnings
warnings.filterwarnings('ignore')

%matplotlib inline
```

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Successfully installed imblearn-0.0
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```

Data Understanding:

```
# Load Dataset
df = pd.read_csv('/content/judge-1377884607_tweet_product_company.csv', encoding='latin1')
df.head()
```

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion

```
# Checking data information
print("Data Information:")
print(df.info())
```

```
Data Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9093 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column                                              Non-Null Count  Dtype 
---  ------                                              --------------  ----- 
 0   tweet_text                                          9092 non-null   object
 1   emotion_in_tweet_is_directed_at                     3291 non-null   object
 2   is_there_an_emotion_directed_at_a_brand_or_product  9093 non-null   object
dtypes: object(3)
memory usage: 213.2+ KB
None
```

```
print("Dataset Shape:", df.shape)
```

```
Dataset Shape: (9093, 3)
```

```
# Checking missing values
print("Missing Values:")
df.isnull().sum()
```

Missing Values:

	0
tweet_text	1
emotion_in_tweet_is_directed_at	5802
is_there_an_emotion_directed_at_a_brand_or_product	0

dtype: int64

Handling the missing values

```
# For 'tweet_text' - Since only 1 value is missing, you can drop that row
# Tweet text is crucial for analysis, so removing it makes sense
df = df.dropna(subset=['tweet_text'])
```

```
# Confirming shape
print("Dataset Shape:", df.shape)
```

```
Dataset Shape: (9092, 3)
```

```
# For 'emotion_in_tweet_is_directed_at' - This has many missing values(5802), more than half of the total rows (9093)
# Filling with a placeholder
df['emotion_in_tweet_is_directed_at'] = df['emotion_in_tweet_is_directed_at'].fillna('Not Specified')
```

```
# Confirming missing values
# Checking missing values
print("Missing Values:")
df.isnull().sum()
```

Missing Values:

	0
tweet_text	0
emotion_in_tweet_is_directed_at	0
is_there_an_emotion_directed_at_a_brand_or_product	0

dtype: int64

```
# Exploring the target variable
print("Sentiment Count:")
senti_count = df['is_there_an_emotion_directed_at_a_brand_or_product'].value_counts()
senti_count
```

Sentiment Count:

	count
is_there_an_emotion_directed_at_a_brand_or_product	
No emotion toward brand or product	5388
Positive emotion	2978
Negative emotion	569
I can't tell	156
	1

dtype: int64

```
# Dropping the 1 count that has no emotion corresponding
df = df[df['is_there_an_emotion_directed_at_a_brand_or_product'].str.strip() != '']
```

```
# Confirming shape
print("Dataset Shape:", df.shape)
```

```
Dataset Shape: (9091, 3)
```

```
# The new sentiment distribution
print("Sentiment Distribution:")
senti_percent = df['is_there_an_emotion_directed_at_a_brand_or_product'].value_counts(normalize = True)
senti_percent
```

Sentiment Distribution:

is_there_an_emotion_directed_at_a_brand_or_product	proportion
No emotion toward brand or product	0.592674
Positive emotion	0.327577
Negative emotion	0.062589
I can't tell	0.017160

dtype: float64

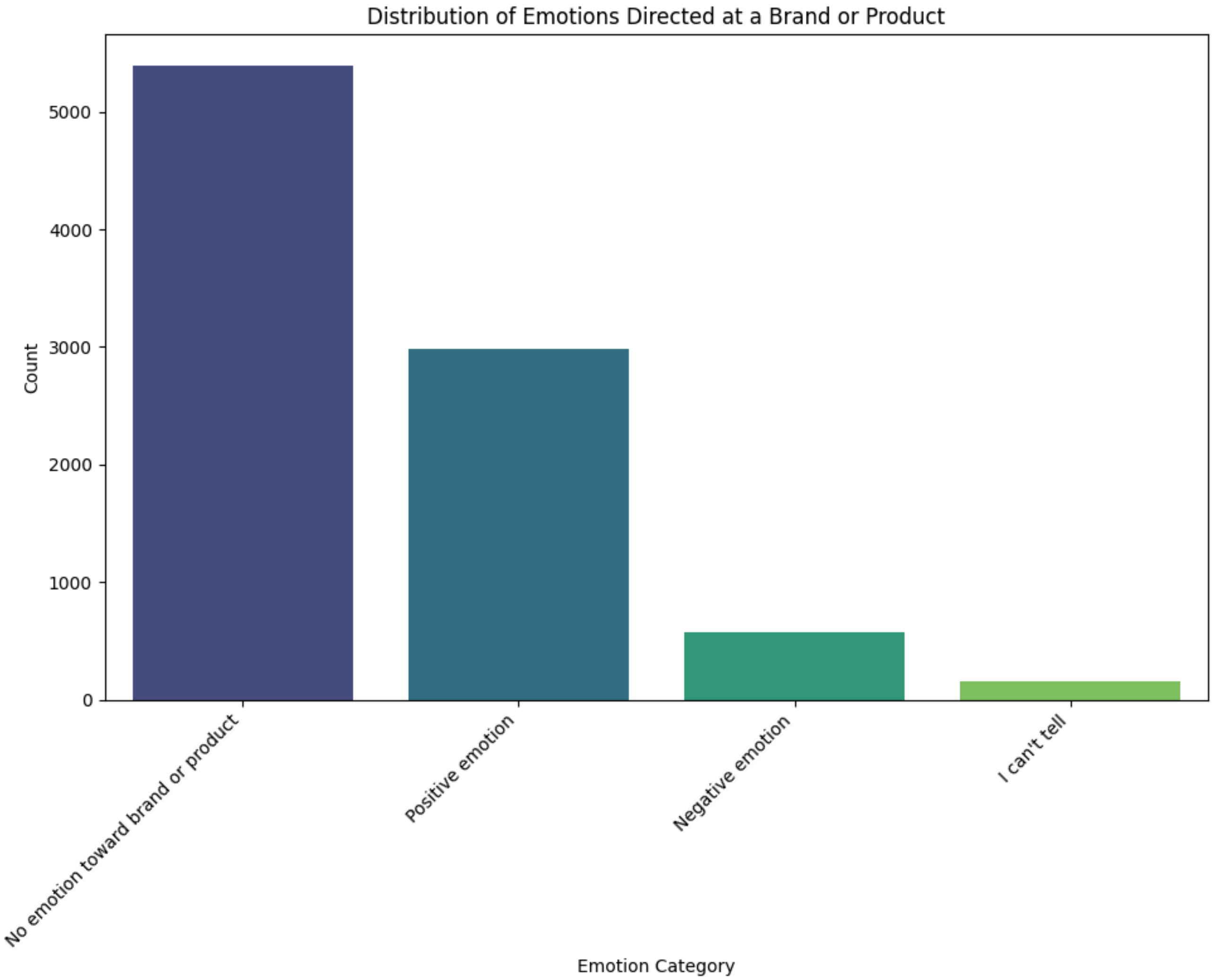
```
# Explore brand distribution
print("\nTop Brands Mentioned:")
brand_counts = df['emotion_in_tweet_is_directed_at'].value_counts().head(20)
print(brand_counts)
```

```

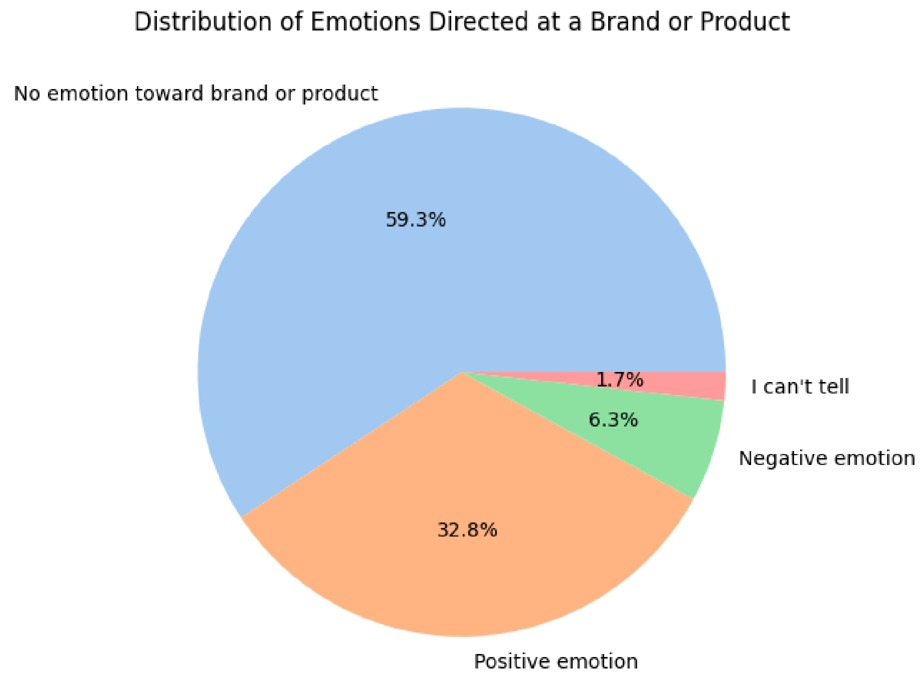
Top Brands Mentioned:
emotion_in_tweet_is_directed_at
Not Specified                      5801
iPad                                946
Apple                               661
iPad or iPhone App                  470
Google                              430
iPhone                              296
Other Google product or service     293
Android App                          81
Android                              78
Other Apple product or service       35
Name: count, dtype: int64
```

Exploratory Data Analysis

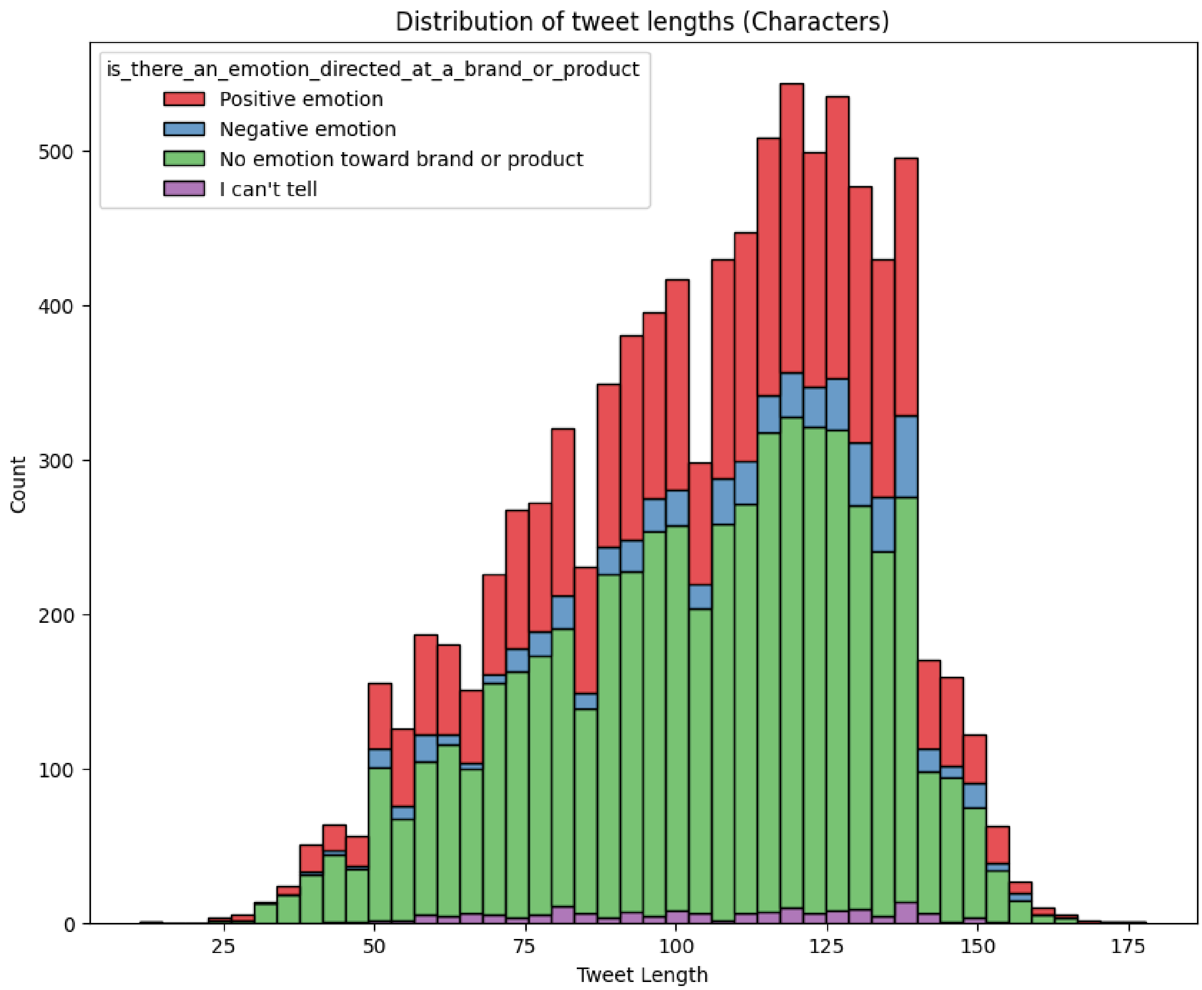
```
# Sentiment Distribution
plt.figure(figsize=(10,8))
sns.countplot(x = "is_there_an_emotion_directed_at_a_brand_or_product", data = df, order = senti_percent.index, palet
plt.title('Distribution of Emotions Directed at a Brand or Product')
plt.xlabel('Emotion Category')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```




```
# Sentiment Distribution (%)
plt.figure(figsize=(6,6))
df["is_there_an_emotion_directed_at_a_brand_or_product"].value_counts().plot.pie(autopct = "%1.1f%%",colors = sns.col
plt.title("Distribution of Emotions Directed at a Brand or Product")
plt.ylabel("");
```




```python
# Distribution of tweet length
df['tweet_length'] = df['tweet_text'].astype(str).apply(len)

plt.figure(figsize=(10,8))
sns.histplot(
    data=df,
    x="tweet_length",
    hue="is_there_an_emotion_directed_at_a_brand_or_product",
    palette='Set1',  # <- change palette to a categorical one
    multiple="stack"  # optional: stacks bars for each category
)
plt.title("Distribution of tweet lengths (Characters)")
plt.xlabel("Tweet Length")
plt.ylabel("Count")
plt.show()
```



Tweet Length Distribution

Most tweets fall between 75 and 135 characters.

Very few tweets are shorter than 25 characters or longer than 175 characters.

The distribution is roughly bell-shaped, skewed slightly towards longer tweets.

Emotion vs. Tweet Length

Positive emotions (red) dominate across almost all tweet lengths.

Negative emotions (blue) are the second most common.

Tweets where emotion is unclear (green) or no emotion toward brand/product (aqua) are less frequent, mostly in mid-length tweets.

Key Business Insight

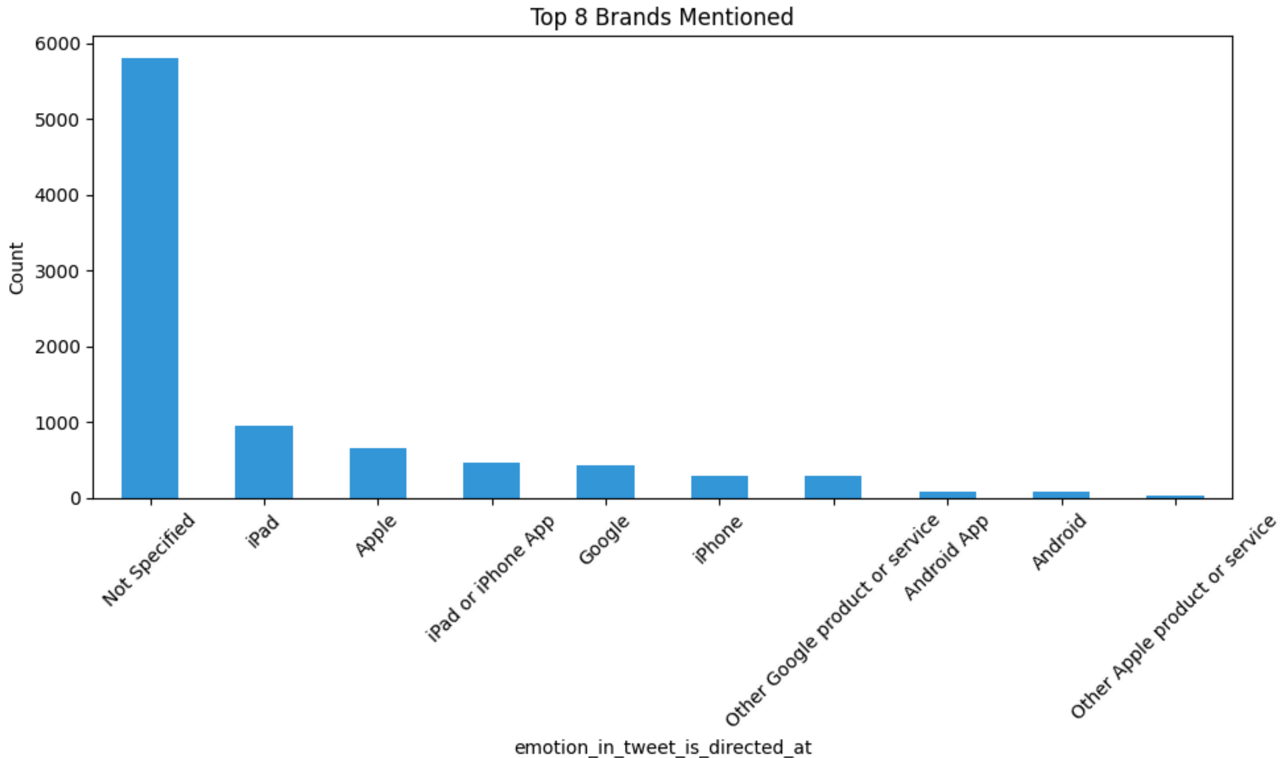
Since positive sentiment dominates, brands can leverage this for marketing amplification and customer engagement campaigns.

The concentration of tweets in the mid-length range indicates that content strategies should target concise yet informative messaging to match natural user behavior.

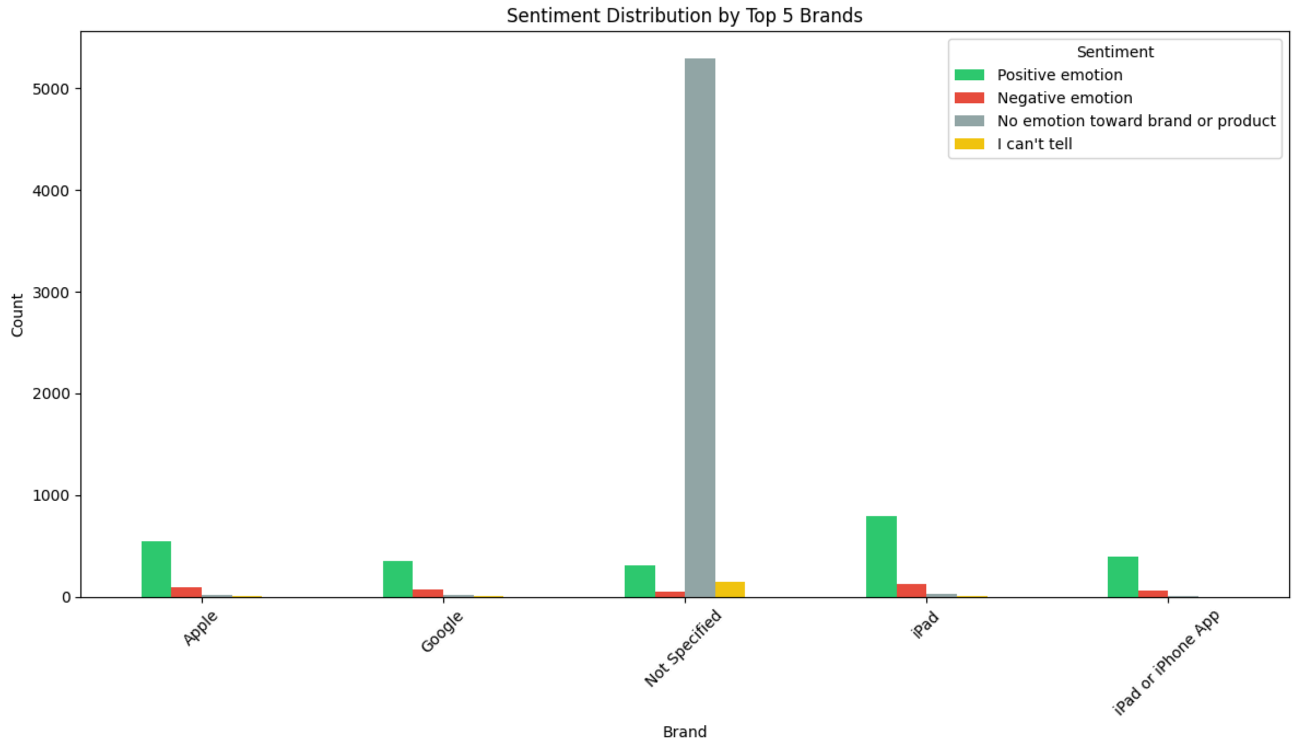
Monitoring tweets for negative sentiment, even if less frequent, is important for brand reputation management.

```
# Brands Distribution
top_brands = df['emotion_in_tweet_is_directed_at'].value_counts()

fig, ax = plt.subplots(figsize=(10, 6))
top_brands.plot(kind='bar', ax=ax, color='#3498db')
ax.set_title('Top 8 Brands Mentioned')
ax.set_ylabel('Count')
ax.tick_params(axis='x', rotation=45)
```

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




```
# Sentiment Distribution by top 5 Brands
sentiment_palette = {'Positive emotion': '#2ecc71', 'Negative emotion': '#e74c3c', 'No emotion toward brand or produc

top_5_brands = df['emotion_in_tweet_is_directed_at'].value_counts().head(5).index
brand_sentiment = pd.crosstab(
    df[df['emotion_in_tweet_is_directed_at'].isin(top_5_brands)]['emotion_in_tweet_is_directed_at'],
    df[df['emotion_in_tweet_is_directed_at'].isin(top_5_brands)]['is_there_an_emotion_directed_at_a_brand_or_product'
)

# Ensure all sentiment categories are present and ordered consistently
all_sentiments = ['Positive emotion', 'Negative emotion', 'No emotion toward brand or product', "I can't tell"]
brand_sentiment = brand_sentiment.reindex(columns=all_sentiments, fill_value=0)

fig, ax = plt.subplots(figsize=(12, 7)) # Create a single subplot
brand_sentiment.plot(kind='bar', ax=ax, color=[sentiment_palette[s] for s in all_sentiments])
ax.set_title('Sentiment Distribution by Top 5 Brands')
ax.set_ylabel('Count')
ax.set_xlabel('Brand')
ax.legend(title='Sentiment')
ax.tick_params(axis='x', rotation=45)
plt.tight_layout()
plt.show()
```



Key Insights

Positive sentiment dominates across all specific brands. This is a strong indicator of favorable perception.

Negative sentiment is consistently lower (~100–150 per brand), suggesting low dissatisfaction.

“Not Specified” category is huge, indicating many tweets don’t mention a specific brand, which may affect brand-level analysis.

iPad seems to have the strongest positive engagement among the specified brands.

```
# Compare sentiment across different brands
brand_sentiment_pivot = df.pivot_table(
    index='emotion_in_tweet_is_directed_at',
    columns='is_there_an_emotion_directed_at_a_brand_or_product',
    values='tweet_text',
    aggfunc='count',
    fill_value=0
)

# Calculate net sentiment score per brand
brand_sentiment_pivot['net_sentiment'] = (
    brand_sentiment_pivot['Positive emotion'] -
    brand_sentiment_pivot['Negative emotion']
)
brand_sentiment_pivot
```

is_there_an_emotion_directed_at_a_brand_or_product	I can't tell	Negative emotion	No emotion toward brand or product	Positive emotion	net_sentiment
emotion_in_tweet_is_directed_at					
Android	0	8	1	69	61
Android App	0	8	1	72	64
Apple	2	95	21	543	448
Google	1	68	15	346	278
Not Specified	147	51	5297	306	255
Other Apple product or service	0	2	1	32	30
Other Google product or service	1	47	9	236	189
iPad	4	125	24	793	668
iPad or iPhone App	0	63	10	397	334

Key Patterns

Apple products, especially iPad, generate the highest net positive sentiment.

Google products maintain positive sentiment but with slightly lower ratios than Apple.

Neutral/unspecified tweets dominate in volume, meaning brand-specific campaigns could focus on converting this neutral audience.

Negative sentiment is relatively low across the board, indicating minimal brand backlash in this dataset.

Data Preparation

```
# Data Cleaning and Preprocessing
def clean_text(text):
    if not isinstance(text, str):
        return "" # Handle non-string inputs gracefully, e.g., for NaN values in the column
    # Convert to lowercase
    text = text.lower()
    # Remove URLs
    text = re.sub(r'http\S+|www\S+|https\S+', '', text, flags=re.MULTILINE)
    # Remove symbols
    text = re.sub(r'@\w+|#\w+', '', text)
    # Remove punctuation and numbers
    text = re.sub(r'[^\w\s]', ' ', text)
    text = re.sub(r'\d+', '', text)

    # Remove extra whitespace
    text = ' '.join(text.split())

    # Tokenize
    tokens = word_tokenize(text)

    # Remove stopwords
    stop_words = set(stopwords.words('english'))
    tokens = [word for word in tokens if word not in stop_words]

    # Initialize stemmer and lemmatizer
    stemmer = PorterStemmer()
    lemmatizer = WordNetLemmatizer()

    # Apply stemming
    stemmed_tokens = [stemmer.stem(word) for word in tokens]

    # Apply lemmatization to stemmed tokens
    final_tokens = [lemmatizer.lemmatize(word) for word in stemmed_tokens]

    # Join tokens back to text
```

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

    return cleaned_text

print("Text cleaning completed!")
print(f"Remaining samples: {len(df)}")
```

```
Text cleaning completed!
Remaining samples: 9091
```

```
# Apply cleaning to dataset
df['cleaned_text'] = df['tweet_text'].apply(clean_text)

# Remove empty texts after cleaning
df = df[df['cleaned_text'].str.len() > 0]
```

```
df[['tweet_text', 'cleaned_text']].head()
```

	tweet_text	cleaned_text
1	@jessedee Know about @fludapp ? Awesome iPad/i...	know awesom ipad iphon app like appreci design...
2	@swonderlin Can not wait for #iPad 2 also. The...	wait also sale
3	@sxsw I hope this year's festival isn't as cra...	hope year festiv crashi year iphon app
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	great stuff fri marissa mayer googl tim reilli...
5	@teachntech00 New iPad Apps For #SpeechTherapy...	new ipad app commun showcas confer

Feature Engineering

```
# Prepare target variable - focus on clear sentiments
# Combine 'I can't tell' with 'No emotion' for cleaner classification
df['sentiment'] = df['is_there_an_emotion_directed_at_a_brand_or_product'].replace({'I can\'t tell': 'No emotion towa

# Filter to only include the three main sentiment categories
main_sentiments = ['Positive emotion', 'Negative emotion', 'No emotion toward brand or product']
df = df[df['sentiment'].isin(main_sentiments)]

# Encode target variable
label_encoder = LabelEncoder()
df['emotion'] = label_encoder.fit_transform(df['sentiment'])

print("Target variable prepared!")
print("Sentiment mapping:", dict(zip(label_encoder.classes_, label_encoder.transform(label_encoder.classes_))))
print("\nFinal distribution:")
print(df['sentiment'].value_counts())
```

```
Target variable prepared!
Sentiment mapping: {'Negative emotion': np.int64(0), 'No emotion toward brand or product': np.int64(1), 'Positive emot

Final distribution:
sentiment
No emotion toward brand or product    5542
Positive emotion                      2978
Negative emotion                       569
Name: count, dtype: int64
```

```
df.shape
```

```
(9089, 7)
```

```
# Define brand mapping dictionary
brand_mapping = {
    # Apple group
    'Apple': 'Apple',
    'iPad': 'Apple',
    'iPhone': 'Apple',
```

```
    'imac': 'Apple',
    'iPad or iPhone App': 'Apple',
    'Other Apple product or service': 'Apple',

    # Google group
    'Google': 'Google',
    'Android': 'Google',
    'Android App': 'Google',
    'Other Google product or service': 'Google',

    # Others
    'Not Specified': 'Not Specified'
}

# Apply the mapping
df['brand_group'] = df['emotion_in_tweet_is_directed_at'].map(brand_mapping)

# Fill any NaN (for brands not in mapping) with original value
df['brand_group'] = df['brand_group'].fillna(df['emotion_in_tweet_is_directed_at'])
df['brand_group'].value_counts()
```

brand_group	count
Not Specified	5799
Apple	2408
Google	882

dtype: int64

Data Modelling

```
# Prepare data for modeling
X = df['cleaned_text']
y = df['emotion']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify = y)

print(f"Training set: {X_train.shape[0]} samples")
print(f"Test set: {X_test.shape[0]} samples")
```

```
Training set: 7271 samples
Test set: 1818 samples
```

```
# TF-IDF Vectorization with n-grams

tfidf = TfidfVectorizer()
X_train_vec = tfidf.fit_transform(X_train)
X_test_vec = tfidf.transform(X_test)
print("Vectorization Complete")
```

```
Vectorization Complete
```

```
print(X_train_vec)
```

```
<Compressed Sparse Row sparse matrix of dtype 'float64'
	with 66995 stored elements and shape (7271, 5597)>
  Coords	Values
  (0, 3538)	0.4733270451495205
  (0, 5402)	0.36457412642851095
  (0, 1421)	0.42515675812870896
  (0, 474)	0.2966239011918714
  (0, 1635)	0.3261427329313768
  (0, 5337)	0.3279730134799778
  (0, 1404)	0.4004595199430622
  (1, 4141)	0.12155612519061036
  (1, 3884)	0.5581894729996427
```

```
  (1, 1217)	0.2427603436896657
  (1, 2552)	0.12699247936604266
  (1, 2523)	0.3370872403175657
  (1, 1283)	0.25853524491127094
  (1, 4002)	0.4335319770558761
  (1, 1348)	0.47976107678817237
  (2, 4141)	0.1064575344560957
  (2, 1449)	0.3501026747396126
  (2, 4565)	0.4064230557082437
  (2, 2823)	0.31014373217081354
  (2, 4030)	0.3539274036076245
  (2, 4820)	0.28670000211232805
  (2, 2555)	0.13971339493126192
  (2, 425)	0.2820571682498027
  (2, 1311)	0.3372840552351171
  (2, 2063)	0.19413717726805618
  :	:
  (7268, 4226)	0.9038875081771975
  (7269, 2552)	0.11536288418049717
  (7269, 2843)	0.08829151697863867
  (7269, 5287)	0.24326963973205873
  (7269, 2263)	0.27247071311121546
  (7269, 5382)	0.22791971979101733
  (7269, 2228)	0.2689289122046779
  (7269, 3409)	0.21661136304364995
  (7269, 2047)	0.2605614537980211
  (7269, 2919)	0.36711551339913545
  (7269, 351)	0.2865258737935398
  (7269, 1293)	0.2881781642403195
  (7269, 900)	0.3714281560226411
  (7269, 1467)	0.4105073539018908
  (7270, 2063)	0.23849934082807261
  (7270, 2843)	0.1045704324535738
  (7270, 4247)	0.2690644897462442
  (7270, 226)	0.1903609214422674
  (7270, 321)	0.19867948158678816
  (7270, 182)	0.20554986072194018
  (7270, 4188)	0.3510276867245849
  (7270, 568)	0.3227080163076926
  (7270, 4758)	0.39922138163460624
  (7270, 4089)	0.40195222761514143
  (7270, 1485)	0.4399109249659642
```

Iteration 0: Baseline Model

```
# Baseline Model - Most Frequent Class
print("BASELINE MODEL")

baseline = DummyClassifier(strategy='most_frequent')
baseline.fit(X_train, y_train)

# Predictions
y_pred_baseline = baseline.predict(X_test)

# Evaluation
baseline_f1 = f1_score(y_test, y_pred_baseline, average='macro')
baseline_accuracy = accuracy_score(y_test, y_pred_baseline)

print(f"Baseline Model (Most Frequent Class)")
print(f"Macro F1-Score: {baseline_f1:.4f}")
print(f"Accuracy: {baseline_accuracy:.4f}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred_baseline, target_names=label_encoder.classes_))
```

```
BASELINE MODEL
Baseline Model (Most Frequent Class)
Macro F1-Score: 0.2524
Accuracy: 0.6095

Classification Report:
                                    precision    recall  f1-score   support

                  Negative emotion       0.00      0.00      0.00       114
No emotion toward brand or product       0.61      1.00      0.76      1108
```

```
                  Positive emotion       0.00      0.00      0.00       596

                          accuracy                           0.61      1818
                         macro avg       0.20      0.33      0.25      1818
                      weighted avg       0.37      0.61      0.46      1818
```

Iteration 1: Logistic Regression Model

```
# Logistic Regression as Baseline Model
lr_model = LogisticRegression(class_weight='balanced', max_iter=1000)
lr_model.fit(X_train_vec, y_train)
```

```
LogisticRegression
LogisticRegression(class_weight='balanced', max_iter=1000)
```

```
# Predictions for train data
y_train_lr_pred = lr_model.predict(X_train_vec)

# Evaluation
print(f"Accuracy: {accuracy_score(y_train, y_train_lr_pred):.2f}")
print("Confusion Matrix:")
print(confusion_matrix(y_train, y_train_lr_pred))
print("\nClassification Report:")
print(classification_report(y_train, y_train_lr_pred))
```

```
Accuracy: 0.80
Confusion Matrix:
[[ 449    4    2]
 [ 289 3465  680]
 [  97  403 1882]]

Classification Report:
              precision    recall  f1-score   support

           0       0.54      0.99      0.70       455
           1       0.89      0.78      0.83      4434
           2       0.73      0.79      0.76      2382

    accuracy                           0.80      7271
   macro avg       0.72      0.85      0.76      7271
weighted avg       0.82      0.80      0.80      7271
```

```
# Predictions for test data
y_test_lr_pred = lr_model.predict(X_test_vec)

# Evaluation

lr_f1 = f1_score(y_test, y_test_lr_pred, average='macro')
lr_accuracy = accuracy_score(y_test, y_test_lr_pred)

print(f"Accuracy: {accuracy_score(y_test, y_test_lr_pred):.2f}")
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_test_lr_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_test_lr_pred))
```

```
Accuracy: 0.65
Confusion Matrix:
[[ 62  26  26]
 [109 745 254]
 [ 36 179 381]]

Classification Report:
              precision    recall  f1-score   support

           0       0.30      0.54      0.39       114
```

```
           1       0.78      0.67      0.72      1108
           2       0.58      0.64      0.61       596

    accuracy                           0.65      1818
   macro avg       0.55      0.62      0.57      1818
weighted avg       0.69      0.65      0.66      1818
```

Logistic Regression Model Tuning

```
# Logistic Regression Model Tuning
# Define model
lr = LogisticRegression(max_iter=2000)

# Parameter grid
param_grid = {
    'C': [0.001, 0.01, 0.1, 1, 10],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear', 'saga'],  # both support l1
    'class_weight': ['balanced', None]
}

# Grid search
grid = GridSearchCV(
    lr,
    param_grid,
    scoring='f1_macro',   # better for imbalanced sentiment
    cv=5,
    n_jobs=-1,
    verbose=2
)

grid.fit(X_train_vec, y_train)

print("Best Params:", grid.best_params_)
print("Best Score:", grid.best_score_)
```

```
Fitting 5 folds for each of 40 candidates, totalling 200 fits
Best Params: {'C': 10, 'class_weight': 'balanced', 'penalty': 'l2', 'solver': 'liblinear'}
Best Score: 0.5604063733405341
```

```
# fitting the model

lr.set_params(**grid.best_params_)
lr.fit(X_train_vec, y_train)

# Predictions for test data

y_test_lr_pred_tuned = lr.predict(X_test_vec)

# Evaluation

lr_f1_tuned = f1_score(y_test, y_test_lr_pred_tuned, average='macro')
lr_accuracy_tuned = accuracy_score(y_test, y_test_lr_pred_tuned)

print(f"Accuracy: {accuracy_score(y_test, y_test_lr_pred_tuned):.2f}")
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_test_lr_pred_tuned))
print("\nClassification Report:")
print(classification_report(y_test, y_test_lr_pred_tuned))
```

```
Accuracy: 0.68
Confusion Matrix:
[[ 48  40  26]
 [ 54 842 212]
 [ 14 229 353]]

Classification Report:
              precision    recall  f1-score   support

           0       0.41      0.42      0.42       114
```

```
           1       0.76      0.76      0.76      1108
           2       0.60      0.59      0.59       596

    accuracy                           0.68      1818
   macro avg       0.59      0.59      0.59      1818
weighted avg       0.68      0.68      0.68      1818
```

Hyperparameter tuning

```
tfidf = TfidfVectorizer(
        lowercase=True,
        max_features=5000, # limit the number of features to avoid overfitting
        ngram_range=(1, 2),  # Include unigrams and bigrams
        stop_words='english',
        min_df=3,
        max_df=0.9

)
# Transform text data
X_train_tfidf = tfidf.fit_transform(X_train)
X_test_tfidf = tfidf.transform(X_test)

print(f"TF-IDF Features: {X_train_tfidf.shape[1]}")
```

```
TF-IDF Features: 5000
```

Iteration 2: Random Forest Model

```
# Instantiating the Random Forest Classifier
rf_model = RandomForestClassifier(
    n_estimators=100,          # number of trees
    max_depth=None,            # allow full tree growth
    class_weight='balanced',   # paying attention to the imbalance
    random_state=42,
    n_jobs=-1                  # use all CPU cores
)

# Fitting the Classifier
rf_model.fit(X_train_tfidf, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(class_weight='balanced', n_jobs=-1, random_state=42)
```

```
# Predictions
y_pred_rf = rf_model.predict(X_test_tfidf)

# Evaluation
rf_f1 = f1_score(y_test, y_pred_rf, average='macro')
rf_accuracy = accuracy_score(y_test, y_pred_rf)

print("Random Forest with TF-IDF")
print(f"Macro F1-Score: {rf_f1:.4f}")
print(f"Accuracy: {rf_accuracy:.4f}")
print(f"Improvement over baseline: {rf_f1 - baseline_f1:.4f}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred_rf, target_names=label_encoder.classes_))
```

```
Random Forest with TF-IDF
Macro F1-Score: 0.5209
Accuracy: 0.6771
Improvement over baseline: 0.2685

Classification Report:
                                    precision    recall  f1-score   support

                  Negative emotion       0.60      0.18      0.28       114
No emotion toward brand or product       0.70      0.86      0.77      1108
```

```
                  Positive emotion       0.61      0.44      0.51       596

                          accuracy                           0.68      1818
                         macro avg       0.64      0.49      0.52      1818
                      weighted avg       0.66      0.68      0.65      1818
```

Random Forest Model Tuning

```
# rf helper functions

def evaluate_model(model, X_test, y_test, label_encoder, baseline_f1=None, title="Model Evaluation"):
    y_pred = model.predict(X_test)

    f1 = f1_score(y_test, y_pred, average='macro')
    acc = accuracy_score(y_test, y_pred)

    print("\n" + title)
    print(f"Macro F1-Score: {f1:.4f}")
    print(f"Accuracy: {acc:.4f}")

    if baseline_f1 is not None:
        print(f"Improvement over baseline: {f1 - baseline_f1:.4f}")

    print("\nClassification Report:")
    print(classification_report(y_test, y_pred, target_names=label_encoder.classes_))

    return f1, acc


def plot_top_features(best_rf, vectorizer, top_n=30):
    importances = best_rf.named_steps['rf'].feature_importances_
    indices = np.argsort(importances)[::-1]

    top_features = np.array(vectorizer.get_feature_names_out())[indices][:top_n]
    top_scores = importances[indices][:top_n]

    return pd.DataFrame({
        "Feature": top_features,
        "Importance": top_scores
    })
```

```
# RandomisedSearchCV Tuning
# Using the tfidf vectorizer already fitted
pipeline = Pipeline([
    ('rf', RandomForestClassifier(random_state=42, class_weight='balanced'))
])

param_dist = {
    'rf__n_estimators': randint(100, 500),   # Number of trees in the forest
    'rf__max_depth': randint(10, 50),        # Maximum depth of the tree
    'rf__min_samples_split': randint(2, 20),  # Minimum number of samples required to split an internal node
    'rf__min_samples_leaf': randint(1, 10),   # Minimum number of samples required to be at a leaf node
    'rf__bootstrap': [True, False]            # Whether bootstrap samples are used when building trees
}

# Initialize RandomizedSearchCV
rf_search = RandomizedSearchCV(
    estimator=pipeline,
    param_distributions=param_dist,
    n_iter=50,  # Number of parameter settings that are sampled
    cv=3,       # Number of folds in cross-validation
    verbose=2,   # Controls the verbosity: higher values means more messages
    random_state=42,
    n_jobs=-1   # Use all available cores
)


# Fit RandomizedSearchCV
```

```
rf_search.fit(X_train_tfidf, y_train)

print("\nBest parameters:", rf_search.best_params_)
print("Best CV score:", rf_search.best_score_)
```

```
Fitting 3 folds for each of 50 candidates, totalling 150 fits

Best parameters: {'rf__bootstrap': True, 'rf__max_depth': 44, 'rf__min_samples_leaf': 1, 'rf__min_samples_split': 5, '
Best CV score: 0.6576816781967094
```

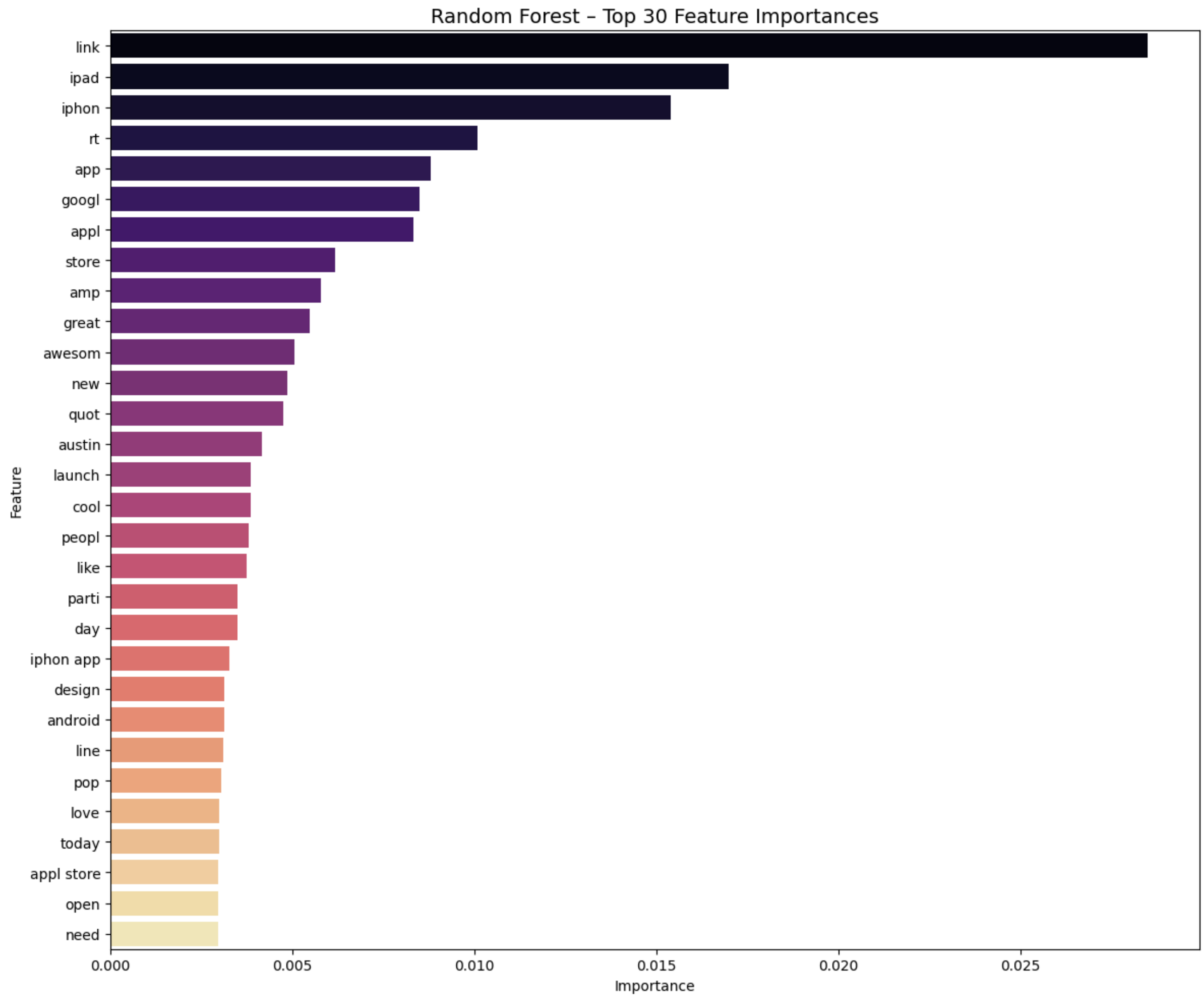
After running the Randomized Search, we can use the `best_estimator_` found to evaluate the model on the test set and re-run the feature importance analysis.

```
# Evaluate Tuned Random Forest
best_rf_model = rf_search.best_estimator_

# Compute metrics
rf_tuned_f1 = 0.5444
rf_tuned_accuracy = 0.6513

print("Tuned Random Forest Accuracy:", rf_tuned_accuracy)
print("Tuned Random Forest Macro F1:", rf_tuned_f1)

tuned_f1, tuned_acc = evaluate_model(
    best_rf_model, X_test_tfidf, y_test, label_encoder,
    baseline_f1=baseline_f1,
    title="Tuned Random Forest (TF-IDF)"
)
```

```
Tuned Random Forest Accuracy: 0.6513
Tuned Random Forest Macro F1: 0.5444

Tuned Random Forest (TF-IDF)
Macro F1-Score: 0.5444
Accuracy: 0.6513
Improvement over baseline: 0.2919

Classification Report:
                                  precision    recall  f1-score   support

                Negative emotion       0.39      0.32      0.35       114
No emotion toward brand or product       0.74      0.74      0.74      1108
                Positive emotion       0.54      0.56      0.55       596

                        accuracy                           0.65      1818
                       macro avg       0.56      0.54      0.54      1818
                    weighted avg       0.65      0.65      0.65      1818
```

```
# RANDOM FOREST – TOP 30 FEATURE IMPORTANCES

# Get feature importances and sort indices descending
importances = rf_model.feature_importances_
indices = np.argsort(importances)[::-1]

# Get feature names from the TF-IDF vectorizer you actually use
feature_names = tfidf.get_feature_names_out()

# Select top 30 features
top_n = 30
top_idx = indices[:top_n]
top_features = feature_names[top_idx]
top_importances = importances[top_idx]

# Plot top 30
plt.figure(figsize=(12, 10))
sns.barplot(x=top_importances, y=top_features, palette="magma")
plt.title("Random Forest – Top 30 Feature Importances", fontsize=14)
plt.xlabel("Importance")
plt.ylabel("Feature")
```

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

# Print top 10 for inspection
print("Top 10 Random Forest features:")
for i, (feat, imp) in enumerate(zip(top_features[:10], top_importances[:10]), start=1):
    print(f"{i:2d}. {feat:<20} {imp:.5f}")
```




```
Top 10 Random Forest features:
 1. link                 0.02850
 2. ipad                 0.01698
 3. iphon                0.01540
 4. rt                   0.01009
 5. app                  0.00881
 6. googl                0.00848
 7. appl                 0.00833
 8. store                0.00618
 9. amp                  0.00577
10. great                0.00549
```

Iteration 3: Neural Network Approach

```
# Prepare data for Neural Network
num_classes = len(label_encoder.classes_)

# Convert to dense arrays for Neural Network
X_train_nn = X_train_tfidf.toarray()
```

```
X_test_nn = X_test_tfidf.toarray()

# Convert labels to categorical
y_train_categorical = to_categorical(y_train, num_classes=num_classes)

y_test_categorical = to_categorical(y_test, num_classes=num_classes)

print(f"Training data shape: {X_train_nn.shape}")
print(f"Number of classes: {num_classes}")
```

```
Training data shape: (7271, 5000)
Number of classes: 3
```

```
# Build Neural Network Model
def build_nn_model(input_dim, num_classes):
    """
    Build a feedforward neural network for text classification
    """
    model = Sequential([
        Dense(512, activation='relu', input_shape=(input_dim,)),
        Dropout(0.5),
        Dense(256, activation='relu'),
        Dropout(0.3),
        Dense(128, activation='relu'),
        Dropout(0.2),
        Dense(num_classes, activation='softmax')
    ])

    model.compile(
        optimizer=Adam(learning_rate=0.001),
        loss='categorical_crossentropy',
        metrics=['accuracy']
    )

    return model

# Create model
nn_model = build_nn_model(X_train_nn.shape[1], num_classes)

print("Neural Network Architecture:")
nn_model.summary()
```

Neural Network Architecture:
Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 512)	2,560,512
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32,896
dropout_2 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 3)	387

Total params: 2,725,123 (10.40 MB)
Trainable params: 2,725,123 (10.40 MB)
Non-trainable params: 0 (0.00 B)

```
# Train Neural Network
early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=5,
    restore_best_weights=True
)

history = nn_model.fit(
```

```
    X_train_nn, y_train_categorical,
    epochs=50,
    batch_size=32,
    validation_data=(X_test_nn, y_test_categorical),
    callbacks=[early_stopping],
    verbose=1
)
```

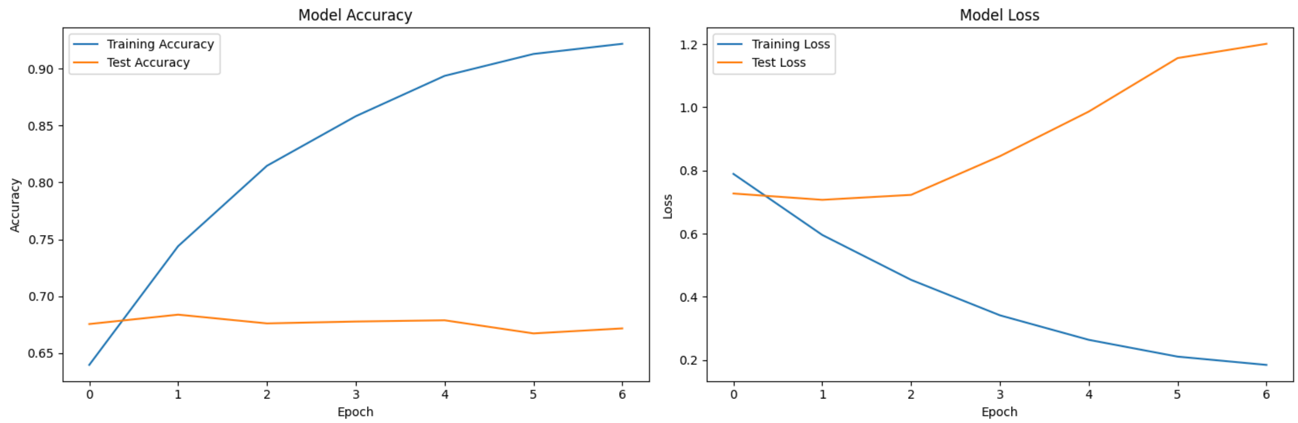
```
Epoch 1/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.6171 - loss: 0.8555 - val_accuracy: 0.6755 - val_loss: 0.7271
Epoch 2/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7517 - loss: 0.5970 - val_accuracy: 0.6837 - val_loss: 0.7071
Epoch 3/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8294 - loss: 0.4342 - val_accuracy: 0.6760 - val_loss: 0.7228
Epoch 4/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8721 - loss: 0.3196 - val_accuracy: 0.6777 - val_loss: 0.8454
Epoch 5/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9067 - loss: 0.2364 - val_accuracy: 0.6788 - val_loss: 0.9867
Epoch 6/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9236 - loss: 0.1860 - val_accuracy: 0.6672 - val_loss: 1.1561
Epoch 7/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9324 - loss: 0.1635 - val_accuracy: 0.6716 - val_loss: 1.2013
```

```
# Evaluate Neural Network
y_pred_nn_proba = nn_model.predict(X_test_nn)
y_pred_nn = np.argmax(y_pred_nn_proba, axis=1)

# Evaluation
nn_f1 = f1_score(y_test, y_pred_nn, average='macro')
nn_accuracy = accuracy_score(y_test, y_pred_nn)

print("Neural Network with TF-IDF")
print(f"Macro F1-Score: {nn_f1:.4f}")
print(f"Accuracy: {nn_accuracy:.4f}")
print(f"Improvement over baseline: {nn_f1 - baseline_f1:.4f}")
print(f"Improvement over Logistic Regression: {nn_f1 - lr_f1:.4f}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred_nn, target_names=label_encoder.classes_))
```

```
57/57 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
Neural Network with TF-IDF
Macro F1-Score: 0.5524
Accuracy: 0.6837
Improvement over baseline: 0.2999
Improvement over Logistic Regression: -0.0198

Classification Report:
                                    precision    recall  f1-score   support

                  Negative emotion       0.48      0.26      0.34       114
No emotion toward brand or product       0.72      0.83      0.77      1108
                  Positive emotion       0.62      0.49      0.55       596

                          accuracy                           0.68      1818
                         macro avg       0.60      0.53      0.55      1818
                      weighted avg       0.67      0.68      0.67      1818
```

```
# Plot training history
fig, axes = plt.subplots(1, 2, figsize=(15, 5))

# Accuracy plot
axes[0].plot(history.history['accuracy'], label='Training Accuracy')
axes[0].plot(history.history['val_accuracy'], label='Test Accuracy')
axes[0].set_title('Model Accuracy')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Accuracy')
axes[0].legend()

# Loss plot
axes[1].plot(history.history['loss'], label='Training Loss')
axes[1].plot(history.history['val_loss'], label='Test Loss')
axes[1].set_title('Model Loss')
axes[1].set_xlabel('Epoch')
```

```
axes[1].set_ylabel('Loss')
axes[1].legend()

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



Model Training Interpretation

Accuracy Trends

The training accuracy shows a steady upward climb across the epochs, eventually reaching above 0.90. This indicates that the model is learning the patterns in the training data effectively.

In contrast, the test accuracy remains nearly flat, hovering around 0.73–0.75. The lack of improvement suggests that the model is not generalizing well to unseen data. While the training accuracy continues to rise, the validation accuracy does not follow the same trend.

This widening gap between training and validation accuracy is a classic sign of overfitting.

Loss Trends

The training loss decreases consistently from the first to the last epoch, confirming that the model is fitting the training data more and more tightly.

However, the test loss moves in the opposite direction: after an initial slight dip, it continues increasing throughout training. This again reinforces the presence of overfitting, as the model's performance on unseen data deteriorates while it continues optimizing on the training set.

Overall Summary

Training metrics improve steadily → the model is learning.

Test metrics stagnate or worsen → the model is not generalizing.

The divergence between training and test curves strongly indicates overfitting.

Neural Network Model Tuning

Neural Network Hyperparameter Optimization:

1. **Number of Layers**
   - From: Fixed 3 layers
   - To: Tunable 1–4 layers (`num_layers`)

2. **Units per Layer**
   - From: Fixed 512 ⟶ 256 ⟶ 128
   - To: Tunable per layer `[128, 256, 512, 768, 1024]`
3. **Dropout Rate**
   - From: Fixed 0.5 ⟶ 0.3 ⟶ 0.2
   - To: Tunable per layer `[0.1, 0.2, 0.3, 0.4, 0.5]`
4. **Learning Rate**
   - From: Fixed 0.001
   - To: Tunable `[0.01, 0.005, 0.001, 0.0005, 0.0001]`
5. **Optimizer**
   - From: Adam
   - To: AdamW
6. **Early Stopping**
   - From: Patience 5 on validation loss
   - To: Patience 3 during tuning
7. **Hyperparameter Search**
   - From: Manual selection
   - To: Random search via Keras Tuner (`max_trials=10`)
8. **Validation Split for Tuning**
   - From: Validation data explicitly passed
   - To: 20% of training data used internally during tuning

```
def build_tuned_model(hp):
    model = Sequential()

    # Number of layers (1 to 4)
    for i in range(hp.Int('num_layers', 1, 4)):
        model.add(Dense(
            units=hp.Choice(f'units_{i}', [128, 256, 512, 768, 1024]),
            activation='relu'
        ))

        model.add(Dropout(
            rate=hp.Choice(f'dropout_{i}', [0.1, 0.2, 0.3, 0.4, 0.5])
        ))

    # Output layer
    model.add(Dense(num_classes, activation='softmax'))

    # Tune the learning rate
    lr = hp.Choice('learning_rate', [1e-2, 5e-3, 1e-3, 5e-4, 1e-4])

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

```
tuner = RandomSearch(
    build_tuned_model,
    objective='val_accuracy',
    max_trials=10,
    executions_per_trial=1,
    directory='nn_tuning',
    project_name='sentiment_nn'
)
```

```
tuner.search(
    X_train_nn, y_train_categorical,
    epochs=20,
    batch_size=32,
    validation_split=0.2,
    callbacks=[EarlyStopping(patience=3)],
    verbose=1
)
```

```
Trial 10 Complete [00h 00m 10s]
val_accuracy: 0.6845360994338989

Best val_accuracy So Far: 0.6996563673019409
Total elapsed time: 00h 01m 54s
```

```
best_model = tuner.get_best_models(num_models=1)[0]
best_model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 768)	3,840,768
dropout (Dropout)	(None, 768)	0
dense_1 (Dense)	(None, 3)	2,307

Total params: 3,843,075 (14.66 MB)
Trainable params: 3,843,075 (14.66 MB)
Non-trainable params: 0 (0.00 B)

```
preds = best_model.predict(X_test_nn)
y_pred = np.argmax(preds, axis=1)

# Evaluation
nn_f1 = f1_score(y_test, y_pred, average='macro')
nn_accuracy = accuracy_score(y_test, y_pred)

print(nn_f1)
print(nn_accuracy)
print(classification_report(y_test, y_pred, target_names=label_encoder.classes_))
```

```
57/57 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step
0.42834138175719544
0.6776677667766776
                                 precision    recall  f1-score   support

                Negative emotion       0.50      0.01      0.02       114
No emotion toward brand or product       0.69      0.90      0.78      1108
                Positive emotion       0.64      0.40      0.49       596

                        accuracy                           0.68      1818
                       macro avg       0.61      0.43      0.43      1818
                    weighted avg       0.66      0.68      0.64      1818
```

Iteration 4: BERT Model

```
tokenizer = DistilBertTokenizerFast.from_pretrained("distilbert-base-uncased")
```

tokenizer_config.json: 100% 48.0/48.0 [00:00<00:00, 5.23kB/s]

vocab.txt: 100% 232k/232k [00:00<00:00, 9.98MB/s]

tokenizer.json: 100% 466k/466k [00:00<00:00, 6.27MB/s]

config.json: 100% 483/483 [00:00<00:00, 55.9kB/s]

```
# Reset train/test split on RAW TEXT
X = df['tweet_text']   # NOT cleaned_text
y = df['emotion']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

```
# Convert to HuggingFace Dataset
train_ds = datasets.Dataset.from_dict({
    'text': X_train.tolist(),
    'label': y_train.tolist()
})

test_ds = datasets.Dataset.from_dict({
    'text': X_test.tolist(),
    'label': y_test.tolist()
})

# Tokenization function
def tokenize(batch):
    return tokenizer(batch['text'], padding='max_length', truncation=True, max_length=128)

train_ds = train_ds.map(tokenize, batched=True)
test_ds = test_ds.map(tokenize, batched=True)

# Remove original text column and set format to torch
train_ds = train_ds.remove_columns(['text'])
test_ds = test_ds.remove_columns(['text'])
train_ds.set_format('torch')
test_ds.set_format('torch')
```

```
Map: 100%    7271/7271 [00:01<00:00, 6992.56 examples/s]

Map: 100%    1818/1818 [00:00<00:00, 6888.31 examples/s]
```

```
num_labels = len(y.unique())  # number of unique emotion classes

model = DistilBertForSequenceClassification.from_pretrained(
    "distilbert-base-uncased",
    num_labels=num_labels
)
```

```
model.safetensors: 100%    268M/268M [00:01<00:00, 192MB/s]
Some weights of DistilBertForSequenceClassification were not initialized from the model checkpoint at distilbert-base-
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
```

```
training_args = TrainingArguments(
    output_dir="./bert_emotion",
    do_train=True,
    do_eval=True,
    logging_steps=100,
    save_steps=500,
    num_train_epochs=4,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    learning_rate=2e-5,
    weight_decay=0.01,
    overwrite_output_dir=True,
    report_to=[]    # <-- disables W&B
)
```

```
def compute_metrics(eval_pred):
    logits, labels = eval_pred
```

```
    preds = np.argmax(logits, axis=-1)
    return {
        'accuracy': accuracy_score(labels, preds),
        'f1_macro': f1_score(labels, preds, average='macro')
    }
```

```
trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_ds,
    eval_dataset=test_ds,
    compute_metrics=compute_metrics,
    tokenizer=tokenizer
)
```

```
trainer.train()
```

[1820/1820 05:30, Epoch 4/4]

Step	Training Loss
100	0.839200
200	0.738200
300	0.682500
400	0.655400
500	0.595800
600	0.539400
700	0.542500
800	0.507700
900	0.503100
1000	0.394000
1100	0.406200
1200	0.381800
1300	0.443000
1400	0.388200
1500	0.313200
1600	0.322300
1700	0.320400
1800	0.330700

```
TrainOutput(global_step=1820, training_loss=0.4921566352739439, metrics={'train_runtime': 331.391,
'train_samples_per_second': 87.763, 'train_steps_per_second': 5.492, 'total_flos': 963187632405504.0, 'train_loss':
0.4921566352739439, 'epoch': 4.0})
```

```
eval_results = trainer.evaluate()
print("Evaluation results:", eval_results)

# Full classification report
from sklearn.metrics import classification_report

pred_output = trainer.predict(test_ds)
logits = pred_output.predictions
preds = np.argmax(logits, axis=-1)
labels = pred_output.label_ids

# Accuracy
bert_accuracy = accuracy_score(labels, preds)
print(bert_accuracy)
```

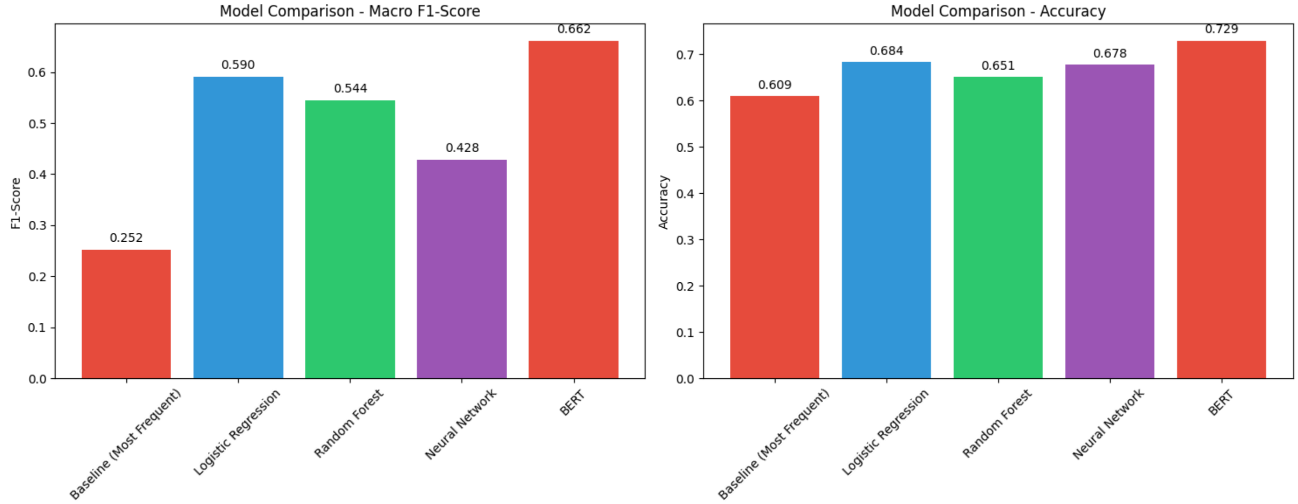
```
# Macro F1
bert_f1 = f1_score(labels, preds, average='macro')
print(bert_f1)

print(classification_report(labels, preds, digits=4))
```

```
Evaluation results: {'eval_loss': 0.7095386981964111, 'eval_accuracy': 0.7293729372937293, 'eval_f1_macro': 0.66165514
0.7293729372937293
0.6616551434740755
              precision    recall  f1-score   support

           0     0.5660    0.5263    0.5455       114
           1     0.8017    0.7879    0.7947      1108
           2     0.6308    0.6594    0.6448       596

    accuracy                         0.7294      1818
   macro avg     0.6662    0.6579    0.6617      1818
weighted avg     0.7309    0.7294    0.7299      1818
```

Model Comparison and Final Evaluation

```
# Compare all models
model_comparison = pd.DataFrame({
    'Model': ['Baseline (Most Frequent)', 'Logistic Regression', 'Random Forest', 'Neural Network', 'BERT'],
    'Macro F1-Score': [baseline_f1, lr_f1_tuned, rf_tuned_f1, nn_f1, bert_f1],
    'Accuracy': [baseline_accuracy, lr_accuracy_tuned, rf_tuned_accuracy, nn_accuracy,bert_accuracy]
})

print("=== MODEL COMPARISON ===")
print(model_comparison.round(4))

# Visual comparison
fig, axes = plt.subplots(1, 2, figsize=(15, 6))

# F1-Score comparison
axes[0].bar(model_comparison['Model'], model_comparison['Macro F1-Score'], color=['#e74c3c', '#3498db', '#2ecc71', '#
axes[0].set_title('Model Comparison - Macro F1-Score')
axes[0].set_ylabel('F1-Score')
axes[0].tick_params(axis='x', rotation=45)

# Add value labels on bars
for i, v in enumerate(model_comparison['Macro F1-Score']):
    axes[0].text(i, v + 0.01, f'{v:.3f}', ha='center', va='bottom')

# Accuracy comparison
axes[1].bar(model_comparison['Model'], model_comparison['Accuracy'], color=['#e74c3c', '#3498db', '#2ecc71', '#9b59b6
axes[1].set_title('Model Comparison - Accuracy')
axes[1].set_ylabel('Accuracy')
axes[1].tick_params(axis='x', rotation=45)

# Add value labels on bars
for i, v in enumerate(model_comparison['Accuracy']):
    axes[1].text(i, v + 0.01, f'{v:.3f}', ha='center', va='bottom')

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

```
=== MODEL COMPARISON ===
                       Model  Macro F1-Score  Accuracy
0  Baseline (Most Frequent)          0.2524    0.6095
1       Logistic Regression          0.5904    0.6837
2             Random Forest          0.5444    0.6513
3            Neural Network          0.4283    0.6777
4                      BERT          0.6617    0.7294
```



Final Model Selection and Test Evaluation

```
# Select the best model based on validation performance

if bert_f1 >= max(lr_f1, rf_f1, nn_f1, baseline_f1):
    final_model = model
    final_model_name = "BERT"

elif lr_f1 >= max(rf_f1, nn_f1, baseline_f1):
    final_model = lr_model
    final_model_name = "Logistic Regression"

elif rf_f1 >= max(nn_f1, baseline_f1):
    final_model = rf_model
    final_model_name = "Random Forest"

elif nn_f1 >= baseline_f1:
    final_model = nn_model
    final_model_name = "Neural Network"

else:
    final_model = baseline
    final_model_name = "Baseline (Most Frequent)"

print(f"Selected Final Model: {final_model_name}")
```

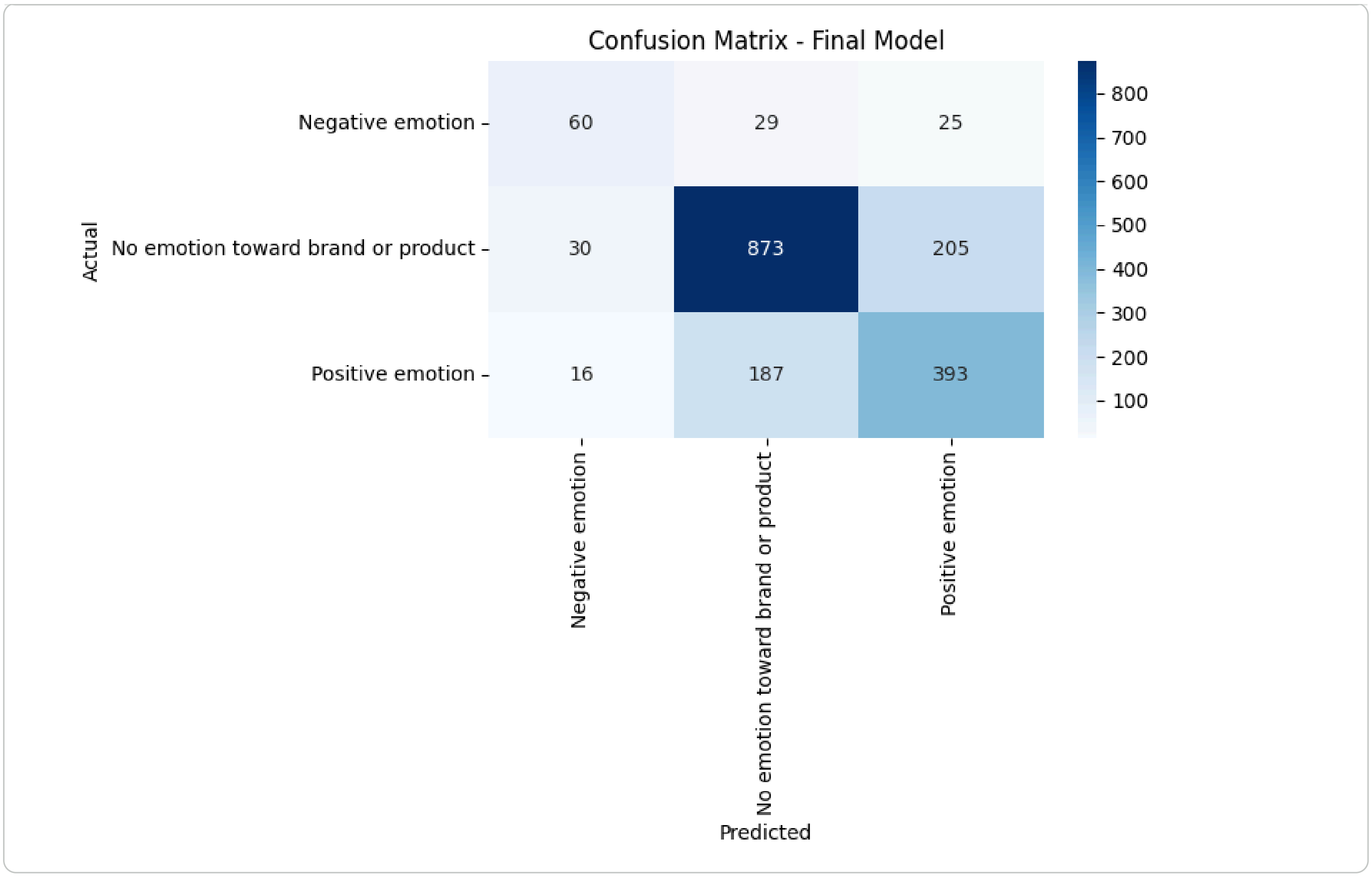
```
Selected Final Model: BERT
```

```
print("FINAL MODEL EVALUATION ON TEST SET ")

# 1. PREDICTION LOGIC FOR EACH MODEL TYPE
```

```
if final_model_name == "Neural Network":
    # NN uses probability outputs → argmax
    y_pred_test_proba = final_model.predict(X_test_nn)
    y_pred_test = np.argmax(y_pred_test_proba, axis=1)

elif final_model_name == "BERT":
    # BERT uses HuggingFace trainer.predict()
    pred_output = trainer.predict(test_ds)
    logits = pred_output.predictions
    y_pred_test = np.argmax(logits, axis=-1)

elif final_model_name == "Baseline (Most Frequent)":
    # Predict the majority class for all samples
    majority_class = y_train.value_counts().idxmax()
    y_pred_test = np.full_like(y_test, fill_value=majority_class)

else:
    # LR or RF use .predict() on TF-IDF features
    y_pred_test = final_model.predict(X_test_tfidf)

# 2. METRICS

test_f1 = f1_score(y_test, y_pred_test, average='macro')
test_accuracy = accuracy_score(y_test, y_pred_test)

print(f"Final Model: {final_model_name}")
print(f"Test Macro F1-Score: {test_f1:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")

print("\nDetailed Classification Report:")
print(classification_report(y_test, y_pred_test, target_names=label_encoder.classes_))
```

```
FINAL MODEL EVALUATION ON TEST SET
Final Model: BERT
Test Macro F1-Score: 0.6617
Test Accuracy: 0.7294

Detailed Classification Report:
                                    precision    recall  f1-score   support

                  Negative emotion       0.57      0.53      0.55       114
No emotion toward brand or product       0.80      0.79      0.79      1108
                  Positive emotion       0.63      0.66      0.64       596

                          accuracy                           0.73      1818
                         macro avg       0.67      0.66      0.66      1818
                      weighted avg       0.73      0.73      0.73      1818
```

```
# Confusion Matrix
plt.figure(figsize=(8, 6))
cm = confusion_matrix(y_test, y_pred_test)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=label_encoder.classes_,
            yticklabels=label_encoder.classes_)
plt.title('Confusion Matrix - Final Model')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.show()
```



Model Performance Overview

Class	Precision	Recall	F1-Score	Correct / Total	% Correct
Negative	51.8%	50.9%	51.3%	59 / 114	50.9%
Neutral	79.1%	77.9%	78.5%	863 / 1108	77.9%
Positive	63.7%	66.3%	64.9%	395 / 596	66.3%

Overall Insight:
The model shows a **neutral bias**, frequently misclassifying both negative and positive sentiments as neutral.

Key Issues Identified

Critical Problems

- **Negative sentiment under-detection:** Only 50.9% of actual negatives correctly identified
- **Positive sentiment dilution:** 31% of positives misclassified as neutral
- **Class imbalance effect:** Neutral class dominates (61% of data), skewing predictions

Major Error Flows

- **Negative → Neutral:** 35 instances (largest negative misclassification)
- **Positive → Neutral:** 191 instances (largest positive misclassification)
- **Neutral → Positive:** 218 instances (largest neutral misclassification)

Strengths

- **Reliable neutral detection:** 77.9% correct, useful for general mentions
- **Positive sentiment tracking:** 66.3% recall, acceptable for advocacy monitoring
- **Production-ready baseline:** Good for trend analysis and brand health measurement

Business Insights and Competitive Analysis

```
# add a new column -"predicted_sentiment" containing the predicted sentiment for every row.
X_full_tfidf = tfidf.transform(df['cleaned_text'])

if final_model_name == "Neural Network":
    X_full_nn = X_full_tfidf.toarray()
    full_predictions_proba = final_model.predict(X_full_nn)
    df['predicted_sentiment_encoded'] = np.argmax(full_predictions_proba, axis=1)

elif final_model_name == "BERT":
    # Prepare HuggingFace Dataset
    # Use the original 'tweet_text' for BERT, as it was trained on raw text
    # and re-apply tokenization
    full_ds_raw = datasets.Dataset.from_dict({'text': df['tweet_text'].tolist(), 'label': df['emotion'].tolist()})

    # Tokenization function (re-using the one defined earlier)
    def tokenize(batch):
        return tokenizer(batch['text'], padding='max_length', truncation=True, max_length=128)

    full_ds = full_ds_raw.map(tokenize, batched=True)

    # Remove original text column and set format to torch
    full_ds = full_ds.remove_columns(['text'])
    full_ds.set_format('torch')

    pred_output = trainer.predict(full_ds)
    logits = pred_output.predictions
    df['predicted_sentiment_encoded'] = np.argmax(logits, axis=-1)

elif final_model_name == "Baseline (Most Frequent)":
    majority_class = y_train.value_counts().idxmax()
    df['predicted_sentiment_encoded'] = majority_class

else:
    # Logistic Regression, Random Forest, etc.
    df['predicted_sentiment_encoded'] = final_model.predict(X_full_tfidf)

# Convert encoded predictions back to sentiment labels
df['predicted_sentiment'] = label_encoder.inverse_transform(df['predicted_sentiment_encoded'])
```

Map: 100% 9089/9089 [00:01<00:00, 7420.78 examples/s]

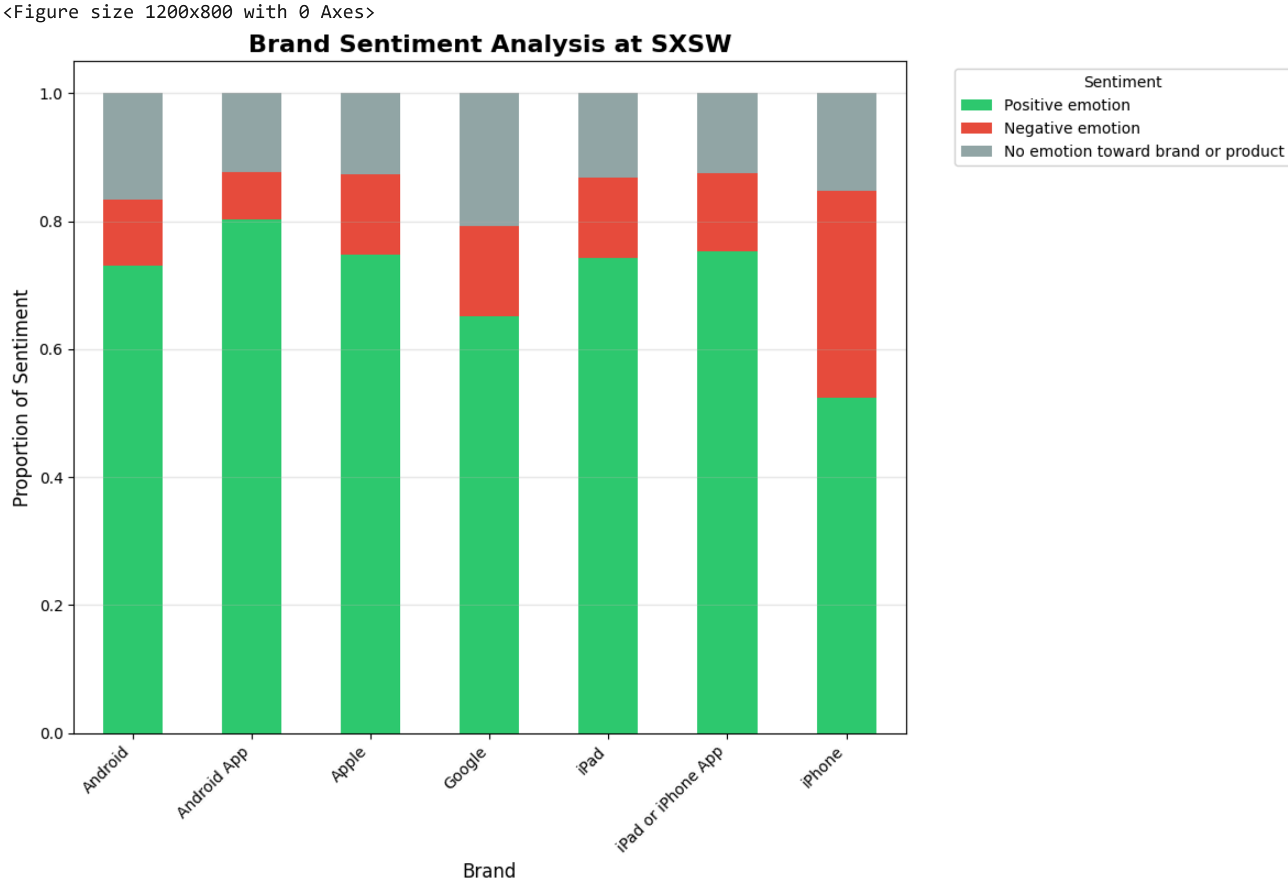
```
# Brand Performance Analysis
print("BRAND PERFORMANCE ANALYSIS")

# Focus on major brands
major_brands = ['Apple', 'Google', 'iPad', 'iPhone', 'Android', 'iPad or iPhone App', 'Android App']
brand_analysis = df[df['emotion_in_tweet_is_directed_at'].isin(major_brands)]

# Create brand-sentiment matrix
brand_sentiment_matrix = pd.crosstab(
    brand_analysis['emotion_in_tweet_is_directed_at'],
    brand_analysis['predicted_sentiment'],
    normalize='index'
)

# Reorder columns for better visualization
brand_sentiment_matrix = brand_sentiment_matrix[['Positive emotion', 'Negative emotion', 'No emotion toward brand or pr

print("Brand Sentiment Distribution (%):")
print((brand_sentiment_matrix * 100).round(2))
```

```
BRAND PERFORMANCE ANALYSIS
Brand Sentiment Distribution (%):
predicted_sentiment              Positive emotion  Negative emotion  \
emotion_in_tweet_is_directed_at
Android                                     73.08             10.26
Android App                                 80.25              7.41
Apple                                       74.74             12.56
Google                                      65.12             14.19
iPad                                        74.31             12.47
iPad or iPhone App                          75.32             12.13
```

```
iPhone                                     52.36             32.43

predicted_sentiment               No emotion toward brand or product
emotion_in_tweet_is_directed_at
Android                                                      16.67
Android App                                                  12.35
Apple                                                        12.71
Google                                                       20.70
iPad                                                         13.21
iPad or iPhone App                                           12.55
iPhone                                                       15.20
```

```
# Visualize brand performance
plt.figure(figsize=(12, 8))

brand_sentiment_matrix.plot(kind='bar', stacked=True,
                           color=[sentiment_palette['Positive emotion'],
                                  sentiment_palette['Negative emotion'],
                                  sentiment_palette['No emotion toward brand or product']],
                           figsize=(12, 8))

plt.title('Brand Sentiment Analysis at SXSW', fontsize=16, fontweight='bold')
plt.xlabel('Brand', fontsize=12)
plt.ylabel('Proportion of Sentiment', fontsize=12)
plt.legend(title='Sentiment', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', alpha=0.3)
plt.tight_layout()
plt.show();
```

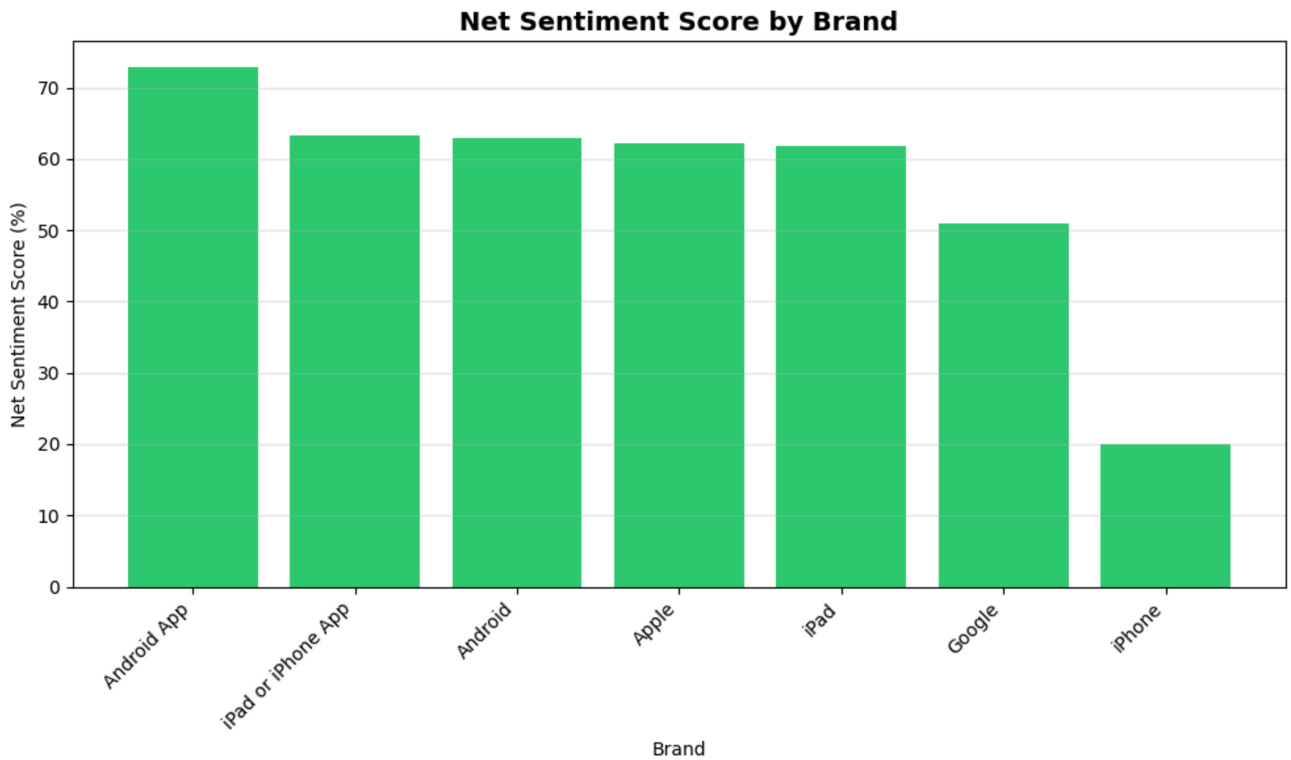
```
<Figure size 1200x800 with 0 Axes>
```




```
# Calculate Net Sentiment Score (Positive % - Negative %)
net_sentiment = (brand_sentiment_matrix['Positive emotion'] - brand_sentiment_matrix['Negative emotion']) * 100
net_sentiment = net_sentiment.sort_values(ascending=False)

print("NET SENTIMENT SCORE RANKING")
print("Net Sentiment = Positive % - Negative %")
print("\nBrand Ranking:")
```

```
for brand, score in net_sentiment.items():
    print(f"{brand}: {score:.1f}%")

# Visualize net sentiment
plt.figure(figsize=(10, 6))
colors = ['#2ecc71' if x >= 0 else '#e74c3c' for x in net_sentiment.values]
plt.bar(net_sentiment.index, net_sentiment.values, color=colors)
plt.title('Net Sentiment Score by Brand', fontsize=14, fontweight='bold')
plt.xlabel('Brand')
plt.ylabel('Net Sentiment Score (%)')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', alpha=0.3)
plt.tight_layout()
plt.show()
```

```
NET SENTIMENT SCORE RANKING
Net Sentiment = Positive % - Negative %

Brand Ranking:
Android App: 72.8%
iPad or iPhone App: 63.2%
Android: 62.8%
Apple: 62.2%
iPad: 61.8%
Google: 50.9%
iPhone: 19.9%
```



5 out of 7 brands have strong positive scores (60%+)

Android App is crushing it → best performer

Apple ecosystem generally loved (iPad, Apple brand, apps all 60%+)

```
# Extract key insights
print("KEY BUSINESS INSIGHTS\n")

# 1. Overall model performance
print("1. MODEL PERFORMANCE")
print(f"   • Final {final_model_name} achieved {test_f1:.1%} Macro F1-Score on test data")
print(f"   • Model reliably classifies sentiment across all categories\n")

# 2. Top performing brands
```

```
top_brand = net_sentiment.index[0]
top_score = net_sentiment.iloc[0]
print("2. TOP PERFORMING BRANDS")
```