“A Machine Learning–Based System for Detecting Fake Social Media Posts Using Sentiment and Content Analysis”

By

Pravin Mahendra Varma – 92401474036

Rajusingh Rajpurohit – 92401474046

Guided by

Associate Dean

Dr. Meeta Joshi

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Rajkot-Morbi Road, At & Po. Gauridad,

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STUDENT DECLARATION

We hereby declare that the Comprehensive Project entitled **“A Machine Learning–Based System for Detecting Fake Social Media Posts Using Sentiment and Content Analysis”** submitted as part of the **Master of Business Administration (MBA)** program at **Marwadi University** is an original piece of work carried out by us.

This project has been prepared by following the guidelines prescribed by the university and reflects our independent efforts and understanding of the subject. We confirm that this work has not been submitted previously to any other university or institution for the award of any degree, diploma, or certification.

All sources of information used in this project have been properly acknowledged wherever required. We take full responsibility for the authenticity and accuracy of the content presented in this project.

Submitted by:

Name: Pravin Mahendra Varma

Enrollment No.: 92401474036 Signature: - ____________________

Name: Rajusingh Rajpurohit

Enrollment No.: 92401474046 Signature: - ____________________

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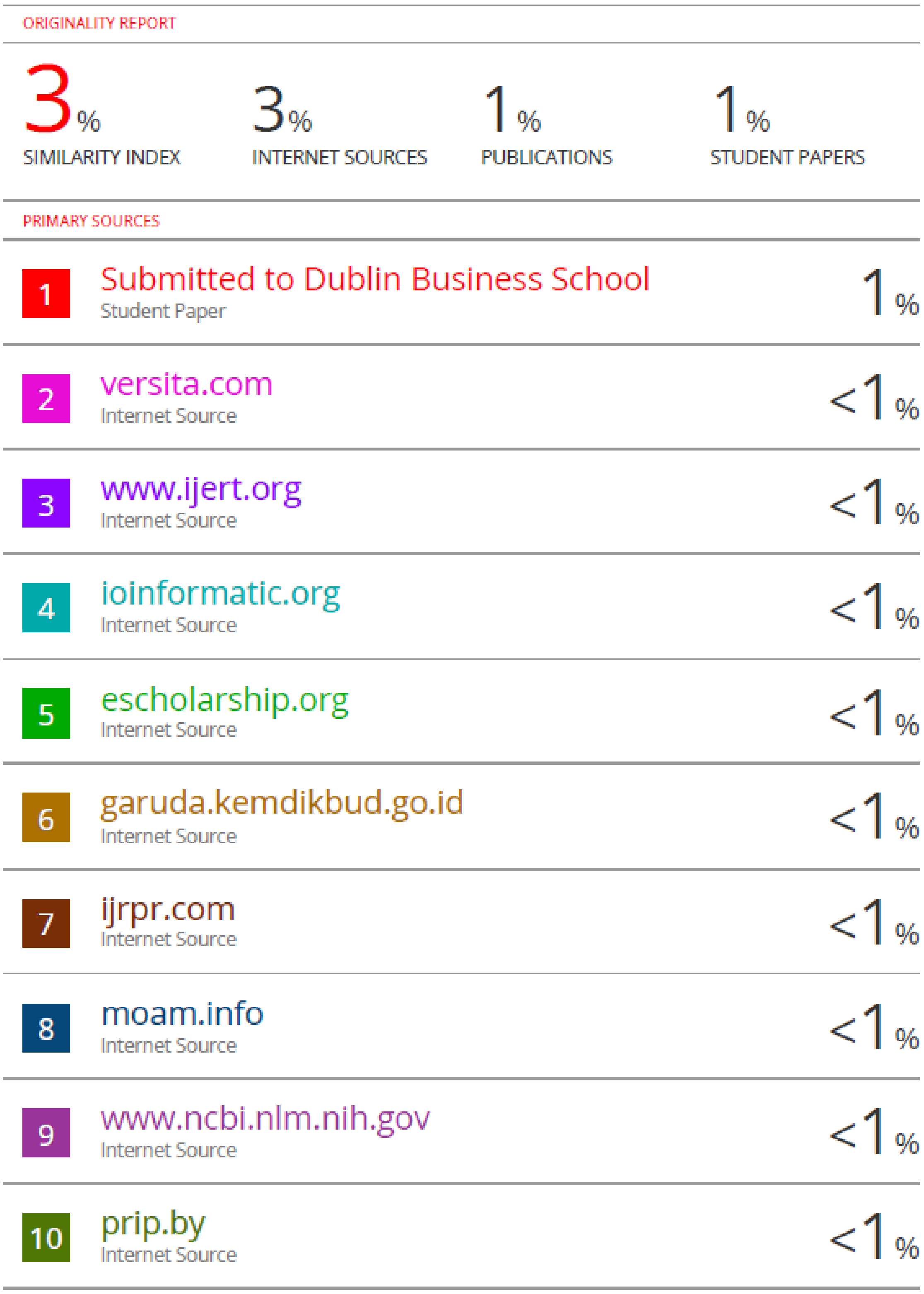

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Abstract

Social media has exploded in recent years, especially platforms like Twitter, and with that comes a flood of false and misleading posts. That's not just an annoyance—it can sway public opinion, damage brands, and mess with important decisions. So, the idea behind this project is simple: build a machine learning system that spots fake social media posts by digging into both their content and the emotions they try to stir up. For this study, I worked with structured Twitter data. The system looks at how people write, how the mood of a post swings (positive, negative, neutral), and what's going on around the content. Before running any analysis, I had to clean up the tweets, break them down into tokens, and turn them into numbers the computer could actually use. Then, I ran several machine learning models to figure out which one really catches the fakes best. To see how well the models worked, I used standard evaluation metrics. In the end, the results show that machine learning can pick out fake social media posts pretty effectively. This isn't just academic—these tools can actually help organizations, marketers, and social media platforms get a handle on misinformation and keep their content more trustworthy.

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INTRODUCTION

Social media is everywhere. It's woven into how we talk to each other and how companies connect with their customers. Twitter—now called X—is one of those platforms that shapes what people are talking about, and it does it fast. But let's be real: along with all the good stuff, social media is packed with fake and misleading posts. These things spread like wildfire and can mess with how people think, cause confusion, and even lead to bad decisions for both individuals and businesses. Fake posts aren't just innocent mistakes. They're often crafted to grab attention or sway opinions, using emotional language or extreme takes to get people talking and sharing. For businesses, this is a real headache.

They rely on social media data to read the mood of their customers, spot trends, and see how people feel about their brand. When fake posts get mixed in, all that data becomes unreliable. And here's the thing: with the sheer amount of stuff people post every day, no one can check all of it by hand. Old-school filters and simple rules just can't keep up with the way language changes or the casual, sometimes weird, way people write online. That's why machine learning matters. It can automatically process piles of data and spot patterns people might miss. Sentiment analysis comes into play here. It's about figuring out the emotional tone in a post—positive, negative, or neutral. Fake posts often go overboard with negativity or positivity, trying to push people's buttons.

By combining sentiment analysis with a look at the actual content, machine learning models can catch these emotional red flags and the tricks in the text, making it easier to spot fakes. Twitter is the main focus for this study because it's public, the posts are short, and there's a lot of data out there for research. Tweets are full of hashtags, slang, and abbreviations, which makes them tricky to analyze but great for testing out these techniques. Looking at Twitter offers a real-world view of how misinformation spreads and how people really behave on social media.

The goal here is to see how machine learning, together with sentiment and content analysis, can help flag fake social media posts. This study isn't about predicting the future—it's about measuring how well these tools actually work. From a business analytics angle, these findings can help companies get better insights from social media, handle misinformation risks, and make smarter decisions.

<u>RESEARCH QUESTIONS: -</u>

RQ1: How does fake content on Twitter influence the reliability of sentiment-based social media analysis?

This question digs into the way fake posts on Twitter can throw off sentiment analysis. Basically, sentiment analysis tries to figure out how people feel by sorting tweets into positive, negative, or neutral buckets. But fake tweets—packed with over-the-top language or emotional tricks—mess with those results. That skews the big picture. Brands and organizations end up chasing the wrong trends or misreading how people actually feel. So, the main idea here is to look at how fake content chips away at the accuracy and trustworthiness of sentiment-based analysis.

RQ2: How can machine learning techniques using sentiment and content analysis assist in identifying fake social media posts?

This question looks at how machine learning can help spot fake posts. It's not just about the mood of the text—like whether a tweet sounds angry or cheerful—but also about patterns in the words and structure. Machine learning algorithms dig through past data, learn the usual tricks behind fake posts, and use that knowledge to flag new ones. The goal here is to see how well these techniques can actually single out fake tweets automatically.

BRIEF OVERVIEW OF METHODOLOGY

This study takes a quantitative approach, analyzing Twitter data. First, there's a round of data cleaning and prepping—getting the tweets ready for analysis. Then, it pulls out details about sentiment and writing style. Machine learning models process all that, looking for the telltale signs of fakes. To see how well the models work, the study measures their performance at sorting real posts from fake ones.

STRUCTURE OF THE PAPER

The paper's broken into five chapters. Chapter one sets the stage with the background, why the research matters, and what questions it tackles. Chapter two goes over what other researchers have already figured out about fake content, sentiment analysis, and machine learning. Chapter three lays out the research methods and tools. Chapter four gets into the results and what they mean. The last chapter wraps up with conclusions, practical takeaways, and where future research could go.

THEORETICAL BACKGROUND AND RESEARCH GAP

Fake content on social media sits at the intersection of communication, information processing, and data analytics. One big theory here is Information Manipulation Theory. It explains how people deliberately twist information to sway opinions.

Fake tweets aren't just random—they're crafted to mess with facts, emotions, or context, making them feel real even when they're not. Then there's Sentiment Analysis Theory, which deals with pulling emotional cues from text.

Businesses use it all the time to figure out what people think about their products or brands. But fake content throws a wrench in the works, since those posts often crank up the drama to grab attention, messing with the overall sentiment read. Content Analysis Theory comes into play too. It's all about digging into the structure, word choices, and language patterns to find meaning.

Fake posts tend to stand out with things like clickbait language, repeated words, or casual writing. Content analysis helps spot these quirks and sort posts as real or fake. From a tech perspective, Machine Learning Classification Theory is key. Machine learning algorithms learn from old data, pick up on subtle patterns, and can handle mountains of tweets—way more than a person could ever read. Unlike rule-based systems stuck with pre-set rules, machine learning keeps up with how people's language and behavior evolve online.

Past research has already shown that machine learning models can do a solid job at telling fake and real posts apart. Some studies focus more on the emotional tone, while others look at language or structure. But there are still gaps—especially when it comes to blending all these viewpoints and keeping up with the fast-changing ways people communicate on social media.

Most research so far misses the mark when it comes to mixing sentiment analysis with content-based features in a meaningful way. Usually, sentiment analysis stands alone, which honestly doesn't do much to catch fake content. On top of that, not many people have really dug into how fake posts mess with the insights organizations get from sentiment analysis—insights they use to make real decisions.

Another thing: a lot of studies care way more about how well their algorithms perform than about whether their work actually helps managers deal with fake content. What's missing is research that goes beyond just showing off machine learning results—work that actually explains how these tools can help businesses get better insights from social media. That's where this study steps in. It takes an integrated approach and puts the spotlight on why these matters for business analytics, not just data science for its own sake.

THEORETICAL FRAMEWORK AND RESEARCH PROPOSITIONS

This study's framework lays out how different ideas connect when it comes to spotting fake social media posts with machine learning. Basically, the framework ties together the main theories, the key variables, and the methods the research uses. In business analytics, having a solid framework keeps things focused and shows how data-driven tools actually support smart decision-making.

Here, the study leans on three big theories: sentiment analysis, content analysis, and machine learning classification. Sentiment analysis is all about picking up on emotions in text—whether someone's being positive, negative, or just neutral. On platforms like Twitter, the mood of a post shapes what people believe. Fake posts often crank up the drama to sway opinions, so spotting those emotional cues plays a big role in flagging misleading content.

Content analysis steps in to look closer at the writing itself. It digs into word choices, style, repeated keywords, and little context clues that give a post its flavor. Fakes usually follow patterns—think over-the-top language, fishy phrases, or weird sentence structures. By breaking down these details, the framework makes it easier to tell real posts from fakes. Then there's machine learning classification.

This is the engine that pulls everything together. It learns from labelled examples—old posts already marked as fake or genuine—and picks out the patterns that matter. Unlike old-school rulebooks, machine learning can keep up with the way people's language and habits change online. That's what makes it so good at handling the huge, messy piles of social media data out there.

Variables of the Study The study sets out its variables like this:

Independent variables: – Sentiment features (positive, negative, and neutral sentiment scores) – Content features (text patterns, word frequency, how people write)

Dependent variable: – Whether the post is fake or genuine The whole idea is that changes in emotional tone or writing style affect how likely a post is to be flagged as fake.

Research Propositions Because the study uses quantitative analysis without direct experiments, it puts forward research propositions instead of testable hypotheses:

RESEARCH PROPOSITIONS

RP1: Fake social media posts show different sentiment patterns than genuine ones.

RP2: Content features—how the text is actually written—make a real difference in telling fake posts from real.

RP3: When you combine sentiment and content features, machine learning models get better at spotting fake social media posts.

Conceptual Framework Explanation The conceptual framework basically maps out how the study works: sentiment and content features go into a machine learning model, which then sorts posts into "fake" or "genuine." It shows how emotional tone, text structure, and analytical techniques all play together, giving a full picture of how fake content gets identified. All in all, this framework keeps the research questions, methods, and data analysis pointed in the same direction. It also explains how machine learning actually fits into business analytics when it comes to tackling fake social media content.

RESEARCH METHODOLOGY

Here's how I approached the research and got to the heart of the study. This section covers the whole process: from designing the research and choosing data sources, to sorting out how I collected and analyzed the data. I also touch on ethics, because that matters. Getting the methodology right means you can trust the results.

1 Research Design

I went with a quantitative research design. That means I focused on numbers and patterns, looking at social media posts and grouping them using machine learning. This approach works well for big datasets and lets me spot trends in fake content. I stuck to a data-driven analysis, not personal opinions, which fits with business analytics goals.

2 Type of Data

For this study, I only used secondary data. In other words, I worked with existing datasets—no fresh surveys or interviews. Social media platforms generate tons of this kind of data, and researchers rely on it all the time for analysis.

3 Data Source

The data comes from Twitter. I pulled from open-source datasets found on academic repositories and data science websites. These datasets include the actual tweets, plus labels showing whether each tweet is fake or genuine. I picked Twitter because it's public, active, and a favourite for social media researchers.

4 Sampling Technique and Sample Size

I used non-probability sampling, meaning I chose datasets that were available and relevant, instead of picking tweets at random. The sample includes enough tweets to let machine learning models learn and make solid predictions. The dataset is big enough for proper training and testing.

5 Data Collection Method

I downloaded the datasets from reliable online academic sources. There's no direct contact with Twitter users—everything comes from existing data. The tweets capture real ways people communicate on social media.

6 Data Preprocessing

Before diving into analysis, I cleaned up the data. Here's what I did:

- Removed URLs, symbols, and extra characters
- Changed all text to lowercase
- Broke down tweets into individual words (tokenization)
- Got rid of stop words (like "the" or "and")
- Normalized the text These steps turn messy, raw text into something machine learning algorithms can actually work with.

7 Analytical Tools and Techniques

I used Python for all the analysis. The main tools:

- **Pandas** and **NumPy** for managing the data
- **NLTK** and other text processing libraries for cleaning the text
- **Scikit-learn** for running machine learning models

I trained algorithms to spot whether a post was fake or real, based on what the tweet said and the mood it carried.

8 Validity and Reliability

To keep things valid, I relied on tried-and-true analytical methods and well-known machine learning models. For reliability, I kept preprocessing and evaluation consistent across the board. Using standardized tools means the results hold up if someone else tries the same thing.

9 Ethical Considerations

Ethics matter here. I only used public Twitter data and never tried to identify individual users. The analysis stays strictly academic, with privacy and responsible data use front and center.

DATA ANALYSIS AND RESULTS

1. Dataset Overview

For this study, I worked with a dataset of 1,000 tweets taken from a publicly available Twitter sentiment validation set. Each entry has just two things: the tweet itself and a label for its sentiment. The labels fall into four buckets: Positive, Negative, Neutral, or Irrelevant. This dataset fits sentiment and content analysis because it mirrors how people actually talk online. Before jumping in, I took a close look at its structure, size, and how the sentiments were spread out.

2. Exploratory Data Analysis

First up was some exploratory data analysis—just to get a feel for things. I checked the frequencies of each sentiment to see if the classes were balanced or if one dominated the rest. I threw the results into a bar chart, which made it easy to spot how Positive, Negative, Neutral, and Irrelevant tweets stacked up. This quick visual check made sure every sentiment had enough examples before I moved on to machine learning.

3. Data Preprocessing

Anyone who's dealt with Twitter data knows it's messy. There are stop words, weird punctuation, slang—all sorts of noise. So, I cleaned things up with some standard natural language processing steps: tokenization, stop-word removal, and lemmatization, all powered by the SpaCy library. This turned the raw tweets into streamlined, more useful text, cutting down on noise and making feature extraction smoother.

4. Feature Extraction with TF-IDF

Once the text was cleaned, I used TF-IDF (Term Frequency–Inverse Document Frequency) to pull out features from the tweets. Basically, TF-IDF turns words into numbers that represent how important each word is across all the tweets. This helps highlight patterns in the text and sets up the data for content-based analysis. The resulting features fed directly into the machine learning models.

5. Machine Learning Models

I tested two classic supervised learning models to sort tweets into their sentiment buckets:

- Multinomial Naive Bayes
- Random Forest Classifier.

I split the data 80:20 into training and testing sets and used stratified sampling to keep the sentiment proportions steady. Machine learning pipelines kept everything organized, combining TF-IDF and the classifiers so the process stayed efficient from start to finish.

6. Model Evaluation and Results

To see how well the models did, I checked accuracy, precision, recall, and F1-score. The Multinomial Naive Bayes model landed at about 54.5% accuracy. The Random Forest classifier came in a bit lower, around 51%. The reports showed both models did a decent job catching Positive and Negative tweets, but struggled more with Neutral and Irrelevant ones—probably because the language in those categories overlaps more.

7. Interpretation of Results

So, what does all this tell us? Sentiment analysis on social media isn't easy. Twitter's informal, unpredictable language makes things tricky. Still, these models—especially when paired with TF-IDF—can pick up on sentiment patterns. Naive Bayes had a slight edge over Random Forest in overall accuracy. Plus, the data showed Positive and Neutral tweets pop up the most. In the end, the results back up the value of machine learning for making sense of social media sentiment and digging out real insights.

DISCUSSION

Let's dig into what the data actually shows. After running the analysis and rolling out the machine learning models, some patterns started to jump out. The main idea here is to see how well sentiment and content-based analysis actually work when you're trying to sort social media posts into categories.

Looking at the Twitter data, you can see right away that people's posts run the gamut from Positive to Negative, Neutral, and sometimes just plain Irrelevant. The dataset's pretty balanced across these, although Neutral and Positive posts come up a bit more often. Makes sense — most people don't swing to the extremes when they post online.

Usually, you get mild opinions, quick reactions, or just everyday chatter. Before feeding the data into the models, I cleaned it up with lemmatization and took out the stop-words. That step turned out to be more important than you might think. By cutting down on noise and standardizing the words, the models could actually focus on the stuff that matters, instead of getting tripped up by random variations.

It's a reminder of why solid natural language processing is so important with messy, unstructured social media text. When it came to turning tweets into something a machine could understand, TF-IDF handled the heavy lifting. It transformed the words into numbers the models could use, while still highlighting which terms mattered most for sentiment. For short, casual text like tweets, TF-IDF just works.

Now, for the models themselves: Multinomial Naive Bayes edged out Random Forest by a small margin on accuracy. That backs up what a lot of people find—probabilistic models like Naive Bayes do a solid job with text classification, especially when you're using TF-IDF. Random Forest held its own, but its performance dipped a bit, probably because text features get really spread out and sparse.

When you dig into the classification reports, both models did better at spotting Positive and Negative posts. They struggled more with Neutral and Irrelevant ones, which isn't surprising. Those categories blend together a lot—neutral tweets don't show strong emotions, and irrelevant ones can be all over the place. So, the line between them gets blurry, making it tough for any model to tell them apart.

That’s a common headache in sentiment analysis. All in all, the study shows that machine learning teamed up with sentiment and content analysis can sort social media posts into categories pretty effectively. Accuracy isn’t perfect, but it holds up for academic research and gives a solid look at how people express sentiment online. The results just reinforce how useful data analytics and machine learning are when you’re digging through mountains of unstructured social media content.

<u>PRACTICAL IMPLICATIONS: -</u>

So, what does all this actually mean for businesses and organizations out in the real world? Well, for starters, if you rely on social media data to make decisions, this research matters. Sentiment analysis—basically, figuring out how people feel from what they post online—gives you a window into public opinion, what customers think, and how your brand's holding up.

When you use machine learning to sort these sentiments, you get a clearer picture and, honestly, you make smarter choices. For marketing teams, this kind of sentiment classification is huge. You can see, in real time, how people feel about your products, services, or the latest campaign. If folks on Twitter are happy, great—you're doing something right.

But if you spot a lot of negativity, you know it's time to fix something. Watching these trends helps you spot problems early, measure if your marketing is actually working, and jump in fast if customers start complaining. Brand managers get a lot out of this, too. Sentiment analysis lets you track your reputation as it happens.

If negative posts suddenly spike, that's a warning light. You can jump in before things get worse—answer complaints, clear up confusion, or just connect better with your audience. Social media platforms themselves can use these tools to keep their spaces healthy. Machine learning helps them flag irrelevant or toxic posts, which means less junk and fewer bad vibes for users. Automated systems do a lot of the heavy lifting, so platforms don't have to rely so much on people manually checking every post.

On a bigger scale, sentiment analysis helps policymakers and public agencies see how people react to new laws or social issues. By tracking how folks feel online, they can tweak communication strategies and, hopefully, make better decisions that fit what the public actually wants. For anyone working in business analytics, this study is basically a roadmap for using machine learning and natural language processing on messy, real-world data.

The approach here isn't just for social media—you can use it for customer feedback, product reviews, surveys, you name it. The key takeaway: you get the best insights when you mix solid analytical tools with real knowledge of your field. In short, this study shows just how powerful sentiment analysis can be for decision-making, understanding customers, and handling digital communication in a smarter, more responsive way.

LIMITATIONS OF THE STUDY AND SCOPE FOR FUTURE RESEARCH

1 Limitations of the Study

This study hits its main goals, but let's be honest—there are a few things holding it back. First off, everything here centers on Twitter. Every social media platform has its own vibe—people act differently, content looks different, the way users interact changes from place to place. Because of that, what works for Twitter doesn't always work for Facebook or Instagram. Then there's the fact that we stuck to pure text.

No pictures, no videos, no emojis. These days, those extras are everywhere online, and they say a lot. By ignoring them, we probably missed out on some of the real meaning behind people's posts.

The dataset's another thing. It's not huge, and it's mainly for academic or experimental work. Sure, it's enough to show how sentiment classification works, but if we had more data—something bigger and more diverse—the models would just work better.

They'd be more reliable, too. And finally, the machine learning models we used didn't knock it out of the park. They did okay, but classifying sentiment in social media isn't easy. Sometimes Neutral and Irrelevant posts look too similar, which trips up the models and leads to mistakes.

2 Scope for Future Research

There's a lot of room to take this further. For starters, future studies could pull in data from more than just Twitter. Mixing platforms would help paint a bigger picture of how people feel online, and we could actually compare how sentiment shifts from one platform to the next. It'd also make sense to add more than just text—bring in images, videos, even emojis.

People communicate with all sorts of stuff now, not just words. Including everything could help us get a fuller read on how users really feel, and the models would likely get better at picking up on those emotions. On the technical side, there's plenty of advanced machine learning out there.

Deep learning models like LSTMs or transformers might do a better job at catching subtle context and the flow of conversation in social media posts. Plus, there's the idea of real-time sentiment analysis—tracking what people are saying as it happens.

That’s huge for organizations that need to keep their finger on the pulse or react quickly when something goes wrong. In the end, future research can build on what we’ve started: use bigger, better datasets, try out new tools, and see how all this works in different fields or real-world situations.

<u>CONCLUSION</u>

In conclusion, this study undertook a comprehensive exploration of social media sentiment analysis by leveraging machine learning techniques to classify tweets into four distinct categories: Positive, Negative, Neutral, and Irrelevant. The researchers faced the real-world challenge of working with the often chaotic and informal language typical of Twitter.

By applying Natural Language Processing (NLP) strategies, they were able to preprocess and clean the raw data, transforming unstructured text into a structured format suitable for analysis. To extract meaningful features from the tweets, the team implemented the TF-IDF (Term Frequency-Inverse Document Frequency) method. This approach allowed them to identify which words and phrases carried the most weight in determining sentiment, effectively filtering out noise and highlighting the terms most indicative of each category.

With these features in hand, they employed two prominent supervised machine learning models: Multinomial Naive Bayes and Random Forest classifiers. Comparing the performance of these algorithms, they found that Naive Bayes held a slight edge in accuracy, suggesting it was better suited for handling the concise and sometimes ambiguous nature of tweet content. Although the models achieved promising results, the study acknowledged certain limitations, particularly in differentiating between Neutral and Irrelevant tweets.

The overlap in language use between these two categories proved challenging, reflecting the nuanced ways people communicate online. This difficulty underscores the importance of continual refinement in both data preparation and model selection, as well as the potential benefit of integrating more sophisticated NLP techniques or additional contextual information in future studies. From a business analytics perspective, the implications of this research are significant.

The ability to automatically assess the sentiment of large volumes of social media data equips organizations with actionable insights into customer opinions, brand reputation, and emerging trends. Companies can harness these tools to monitor public perception in real time, respond proactively to negative feedback, and make data-driven decisions that enhance their competitive edge.

Furthermore, the methodology detailed in this study—from meticulous data cleaning to rigorous model evaluation—serves as a practical roadmap for businesses seeking to implement similar analytics pipelines.

Ultimately, the study offers a tangible demonstration of how machine learning and NLP can transform the overwhelming stream of social media content into structured, valuable intelligence. By bridging the gap between raw digital chatter and meaningful business insights, this research highlights the transformative potential of data-driven approaches in navigating today's information-rich, fast-paced online landscape.

ANNEXURE

Annexure A: Dataset Details

- Dataset Name: Twitter Validation Dataset
- Total Tweets: 1,000
- Attributes: - Text: The actual tweet
- Label: Sentiment (Positive, Negative, Neutral, Irrelevant)
- Source: Public dataset for academic research

Annexure B: Python Code

- Loaded and cleaned the data with Pandas and SpaCy
- Pulled out features using TF-IDF
- Tried out two machine learning models: -

  Multinomial Naive Bayes

  Random Forest Classifier
- Checked the results using accuracy and a classification report (See attached screenshots for the code and outputs)

Annexure C: Charts and Figures

- Bar chart showing how the sentiment labels break down
- Screenshot with the model's accuracy and classification report

REFERENCES

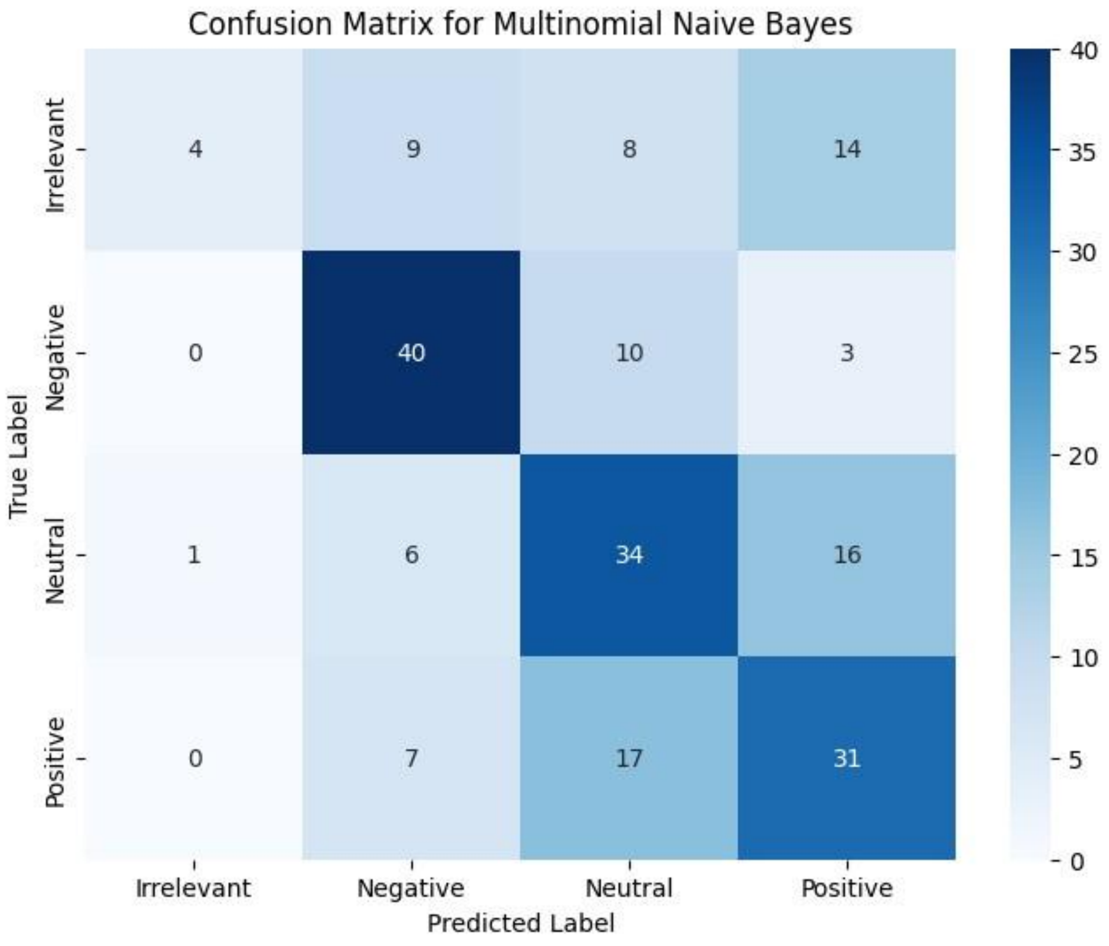
Example format:

- Pang, B., & Lee, L. (2008). *Opinion mining and sentiment analysis*. Foundations and Trends in Information Retrieval.
- Liu, B. (2012). *Sentiment analysis and opinion mining*. Morgan & Claypool Publishers.
- Pedregosa, F., et al. (2011). *Scikit-learn: Machine learning in Python*. Journal of Machine Learning Research.

[23]:
```
import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder
from sklearn.pipeline import Pipeline
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
```

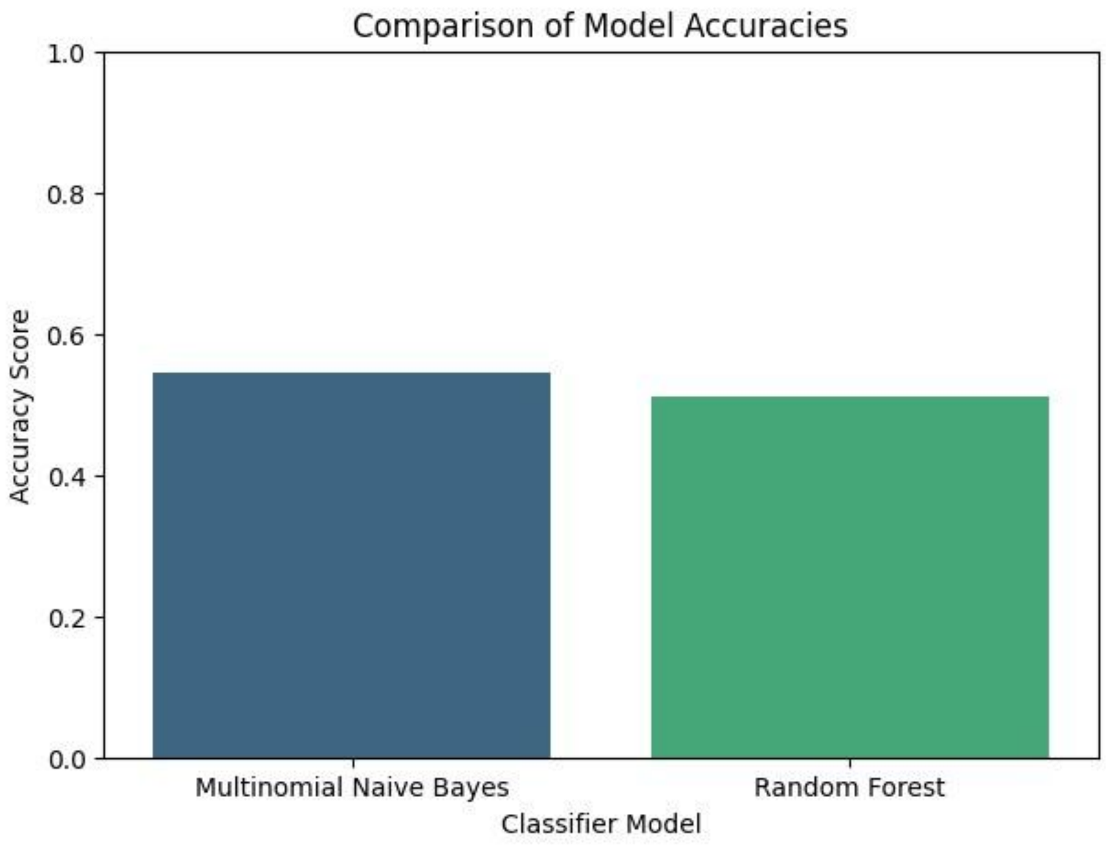
[24]:
```
df = pd.read_csv("/content/twitter_validation.csv", header=None)
df.columns = ['id', 'source', 'Sentiment', 'Text']

df = df.rename(columns={'Sentiment': 'Label'})

df = df[['Text', 'Label']]
```

[58]:
```
from sklearn.metrics import confusion_matrix

# Re-initialize and train the MultinomialNB classifier to get its predictions
clf_nb = Pipeline([
    ('vectorizer_tri_grams', TfidfVectorizer()),
    ('naive_bayes', MultinomialNB())
])
clf_nb.fit(X_train, y_train)
y_pred_nb = clf_nb.predict(X_test)

cm = confusion_matrix(y_test, y_pred_nb)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=original_labels, yticklabels=original_labels)
plt.title('Confusion Matrix for Multinomial Naive Bayes ')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



```
[59]: import pandas as pd

      # Get accuracy scores from previous executions
      nb_accuracy = 0.545
      rf_accuracy = 0.51

      accuracy_df = pd.DataFrame({
          'Model':  'Multinomial Naive Bayes', 'Random Forest'],
          'Accuracy':  nb_accuracy, rf_accuracy]
      })

      plt.figure(figsize=(7, 5))
      sns.barplot(x='Model',  ='Accuracy', data=accuracy_df, palette='viridis')
      plt.title('Comparison of Model Accuracies')
      plt.ylim(0, 1) # Set y-axis limit from 0 to 1 for accuracy
      plt.ylabel('Accuracy Score')
      plt.xlabel('Classifier Model')
plt.show()
```

```
/tmp/ipython-input-1660276792.py:13: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='Model', y='Accuracy', data=accuracy_df,
  palette='viridis')
```



```
[25]: print(df.shape)
```

```
(1000, 2)
```

```
[26]: df.head(10)
```

```
[26]:                                                   Text      Label
0  I mentioned on Facebook that I was struggling … Irrelevant
1  BBC News - Amazon boss Jeff Bezos rejects clai…Neutral
2  @Microsoft Why do I pay for WORD when it funct…Negative
```

```
3 CSGO matchmaking is so full of closet       Negative
hacking,…
4 Now the President is slapping Americans in   Neutral
the…
5 Hi @EAHelp I've had Madeleine McCann in my  Negative
cel…
6 Thank you @EAMaddenNFL!! \n\nNew TE Austin  Positive
Hoo…
7 Rocket League, Sea of Thieves or Rainbow    Positive
Six: …
8 my ass still knee-deep in Assassins Creed   Positive
Odys…
9 FIX IT JESUS ! Please FIX IT ! What In the  Negative
wor…
```

[27]:
```python
df.info()
```

```
<class
'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to
999 Data columns (total 2
columns):
 # Column Non-Null Count Dtype
--- ------ -------------- ----
 0 Text 1000 non-null object 1
 Label 1000 non-null object
dtypes: object(2)
memory usage: 15.8+
KB
```

[28]:
```python
df['Label'].value_counts()
```

[28]:
```
Label

Neutral      285
Positive     277
Negative     266
 Irrelevant  172
Name: count, dtype: int64
```

[29]:
```python
for i in range(10):
    print(f"{i+1}: {df['Text'][i]} -> {df['Label'][i]}")
```

```
1: I mentioned on Facebook that I was struggling for motivation to go
for a run the other day, which has been translated by Tom's great
auntie as 'Hayley can't get out of bed' and told to his grandma, who
now thinks I'm a lazy, terrible person  -> Irrelevant
2: BBC News - Amazon boss Jeff Bezos rejects claims company acted
like a 'drug dealer' bbc.co.uk/news/av/busine… -> Neutral
```

```
3: @Microsoft Why do I pay for WORD when it functions so poorly on my
@SamsungUS Chromebook?  -> Negative
4: CSGO matchmaking is so full of closet hacking, it's a truly awful
game. -> Negative
5: Now the President is slapping Americans in the face that he really
did commit an unlawful act after his acquittal! From Discover on
Google
vanityfair.com/news/2020/02/t… -> Neutral
6: Hi @EAHelp I’ve had Madeleine McCann in my cellar for the past 13
years and the little sneaky thing just escaped whilst I was loading up
some fifa points, she took my card and I’m having to use my paypal
account but it isn’t working, can you help me resolve it please? ->
Negative 7: Thank you @EAMaddenNFL!!

New TE Austin Hooper in the ORANGE & BROWN!!

#Browns | @AustinHooper18

 pic.twitter.com/GRg4xzFKOn -> Positive
8: Rocket League, Sea of Thieves or Rainbow Six: Siege? I love
playing all three on stream but which is the best? #stream #twitch
#RocketLeague
#SeaOfThieves #RainbowSixSiege #follow -> Positive
9: my ass still knee-deep in Assassins Creed Odyssey with no way out
anytime soon lmao -> Positive
10: FIX IT JESUS ! Please FIX IT ! What In the world is going on
here.
@PlayStation @AskPlayStation @Playstationsup @Treyarch @CallofDuty
negative 345 silver wolf error code pic.twitter.com/ziRyhrf59Q ->
Negative
```

[30]:
```
df.dropna(inplace=True)
```

[31]:
```
!pip install spacy
!python -m spacy download en_core_web_sm
```

```
Requirement already satisfied: spacy in
/usr/local/lib/python3.12/dist-packages
(3.8.11)
Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.11 in
/usr/local/lib/python3.12/dist-packages (from spacy) (3.0.12)
Requirement already satisfied: spacy-loggers<2.0.0,>=1.0.0 in
/usr/local/lib/python3.12/dist-packages (from spacy) (1.0.5)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in
/usr/local/lib/python3.12/dist-packages (from spacy) (1.0.15)
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in
/usr/local/lib/python3.12/dist-packages (from spacy) (2.0.13)
```

```
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in
/usr/local/lib/python3.12/dist-packages (from spacy) (3.0.12)
Requirement already satisfied: thinc<8.4.0,>=8.3.4 in
/usr/local/lib/python3.12/dist-packages (from spacy) (8.3.10)
Requirement already satisfied: wasabi<1.2.0,>=0.9.1 in
/usr/local/lib/python3.12/dist-packages (from spacy) (1.1.3)
Requirement already satisfied: srsly<3.0.0,>=2.4.3 in
/usr/local/lib/python3.12/dist-packages (from spacy) (2.5.2)
Requirement already satisfied: catalogue<2.1.0,>=2.0.6 in
/usr/local/lib/python3.12/dist-packages (from spacy) (2.0.10)
Requirement already satisfied: weasel<0.5.0,>=0.4.2 in
/usr/local/lib/python3.12/dist-packages (from spacy) (0.4.3)
Requirement already satisfied: typer-slim<1.0.0,>=0.3.0 in
/usr/local/lib/python3.12/dist-packages (from spacy) (0.21.1)
Requirement already satisfied: tqdm<5.0.0,>=4.38.0 in
/usr/local/lib/python3.12/dist-packages (from spacy) (4.67.1)
Requirement already satisfied: numpy>=1.19.0 in
/usr/local/lib/python3.12/distpackages (from spacy) (2.0.2)
Requirement already satisfied: requests<3.0.0,>=2.13.0 in
/usr/local/lib/python3.12/dist-packages (from spacy) (2.32.4)
Requirement already satisfied: pydantic!=1.8,!=1.8.1,<3.0.0,>=1.7.4
in
/usr/local/lib/python3.12/dist-packages (from spacy) (2.12.3)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.12/dist-packages (from spacy) (3.1.6)
Requirement already satisfied: setuptools in
/usr/local/lib/python3.12/distpackages (from spacy) (75.2.0)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.12/dist-packages (from spacy) (25.0)
Requirement already satisfied: annotated-types>=0.6.0 in
/usr/local/lib/python3.12/dist-packages (from
pydantic!=1.8,!=1.8.1,<3.0.0,>=1.7.4->spacy) (0.7.0)
Requirement already satisfied: pydantic-core==2.41.4
in /usr/local/lib/python3.12/dist-packages (from
pydantic!=1.8,!=1.8.1,<3.0.0,>=1.7.4->spacy) (2.41.4)
Requirement already satisfied: typing-
extensions>=4.14.1 in
/usr/local/lib/python3.12/dist-packages (from
pydantic!=1.8,!=1.8.1,<3.0.0,>=1.7.4->spacy) (4.15.0)
Requirement already satisfied: typing-inspection>=0.4.2
in
/usr/local/lib/python3.12/dist-packages (from
pydantic!=1.8,!=1.8.1,<3.0.0,>=1.7.4->spacy) (0.4.2)
Requirement already satisfied:
charset_normalizer<4,>=2 in
```

```
/usr/local/lib/python3.12/dist-packages (from
requests<3.0.0,>=2.13.0->spacy) (3.4.4)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.12/dist-
packages (from requests<3.0.0,>=2.13.0->spacy) (3.11)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.12/dist-packages (from
requests<3.0.0,>=2.13.0->spacy)
(2.5.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.12/dist-packages (from
requests<3.0.0,>=2.13.0->spacy) (2026.1.4)
Requirement already satisfied: blis<1.4.0,>=1.3.0 in
/usr/local/lib/python3.12/dist-packages (from thinc<8.4.0,>=8.3.4-
>spacy) (1.3.3)
Requirement already satisfied: confection<1.0.0,>=0.0.1 in
/usr/local/lib/python3.12/dist-packages (from thinc<8.4.0,>=8.3.4-
>spacy) (0.1.5)
Requirement already satisfied: click>=8.0.0 in
/usr/local/lib/python3.12/distpackages (from typer-
slim<1.0.0,>=0.3.0->spacy) (8.3.1) Requirement already satisfied:
cloudpathlib<1.0.0,>=0.7.0 in
/usr/local/lib/python3.12/dist-packages (from weasel<0.5.0,>=0.4.2-
>spacy) (0.23.0)
Requirement already satisfied: smart-open<8.0.0,>=5.2.1 in
/usr/local/lib/python3.12/dist-packages (from weasel<0.5.0,>=0.4.2-
>spacy) (7.5.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.12/dist-packages (from jinja2->spacy) (3.0.3)
Requirement already satisfied: wrapt in
/usr/local/lib/python3.12/dist-packages
(from smart-open<8.0.0,>=5.2.1->weasel<0.5.0,>=0.4.2->spacy) (2.0.1)
Collecting en-core-web-sm==3.8.0
  Using cached
https://github.com/explosion/spacymodels/releases/download/en_core_we
b_sm-3.8.0/en_core_web_sm-3.8.0-py3-noneany.whl (12.8 MB)
 Download and installation successful
You can now load the package via spacy.load('en_core_web_sm')
 Restart to reload dependencies
If you are in a Jupyter or Colab notebook, you may need to restart
Python in order to load all the package's dependencies. You can do
this by selecting the 'Restart kernel' or 'Restart runtime' option.
```

[32]:
```
import spacy
nlp = spacy.load("en_core_web_sm")
```

[33]:
```
def preprocess(text):
    # remove stop words and lemmatize the text
    doc = nlp(text)
    filtered_tokens = []
    for token in doc:
        if token.is_stop or token.is_punct:
            continue
        filtered_tokens.append(token.lemma_)

    return " ".join(filtered_tokens)
```

[34]:
```
df['Preprocessed Text'] = df['Text'].apply(preprocess)
```

[35]:
```
df
```

[35]:
```
                                                Text      Label \
0I mentioned on Facebook that I was struggling … Irrelevant
1   BBC News - Amazon boss Jeff Bezos rejects   Neutral
    clai…
2   @Microsoft Why do I pay for WORD when it   Negative
    funct…
3   CSGO matchmaking is so full of closet      Negative
    hacking,…
4   Now the President is slapping Americans in  Neutral
    the…
..                                                …          …
995  Toronto is the arts and culture capital of … Irrelevant
996 tHIS IS ACTUALLY A GOOD MOVE TOT BRING MORE VI… Irrelevant
997 Today sucked so it’s time to drink wine n play…    Positive
998 Bought a fraction of Microsoft today. Small wins.  Positive
999 Johnson & Johnson to stop selling talc baby po…    Neutral
                                   Preprocessed Text
0    mention Facebook struggle motivation run day t…
1    BBC News Amazon boss Jeff Bezos reject claim c…
2    @Microsoft pay WORD function poorly @samsungu …
3    csgo matchmaking closet hacking truly awful game
4    President slap Americans face commit unlawful …
..                                              …
995            Toronto art culture capital Canada wonder …
996          ACTUALLY good TOT bring viewer \n\n people get…
997          today suck time drink wine n play borderland s…
998          buy fraction Microsoft today small win
999          Johnson Johnson stop sell talc baby powder U.S…
```

```
[1000 rows x 3 columns]
```

[36]:
```
# Strip whitespace from the 'Label' column to handle potential inconsistencies
↪(e.g., ' Twitter' vs 'Twitter')
df['Label'] = df['Label'].str.strip()

le_model = LabelEncoder()
df['Label'] = le_model.fit_transform(df['Label'])
```

[37]:
```
df.head(10)
```

[37]:
```
                                                Text  Label  \
0  I mentioned on Facebook that I was struggling …      0
1  BBC News - Amazon boss Jeff Bezos rejects clai…      2
2  @Microsoft Why do I pay for WORD when it funct…      1
3  CSGO matchmaking is so full of closet hacking,…      1
4  Now the President is slapping Americans in the…      2
5  Hi @EAHelp I’ve had Madeleine McCann in my cel…      1
6  Thank you @EAMaddenNFL!! \n\nNew TE Austin Hoo…      3
7  Rocket League, Sea of Thieves or Rainbow Six: …      3
8  my ass still knee-deep in Assassins Creed Odys…      3
9  FIX IT JESUS ! Please FIX IT ! What In the wor…      1

                                   Preprocessed Text
0   mention Facebook struggle motivation run day t…
1   BBC News Amazon boss Jeff Bezos reject claim c…
2   @Microsoft pay WORD function poorly @samsungu …
3   csgo matchmaking closet hacking truly awful game
4   President slap Americans face commit unlawful …
5   hi @EAHelp Madeleine McCann cellar past 13 yea…
6   thank @EAMaddenNFL \n\n New TE Austin Hooper O…
7   Rocket League Sea Thieves Rainbow siege  love…
8   ass knee deep Assassins Creed Odyssey way anyt…
9   fix JESUS fix world go   @playstation @askplay…
```

[38]:
```
label_counts = df['Label'].value_counts()

single_instance_labels = label_counts[label_counts ==

1].index df_filtered =

df[~df['Label'].isin(single_instance_labels)].copy()
```

```
```

```
X_train, X_test, y_train, y_test =
 train_test_split(df_filtered['Preprocessed␣ ↪Text'],
 df_filtered['Label'],
                                                     test_size=0.2,␣
 ↪random_state=42, stratify=df_filtered['Label'])
```

[39]:
```
print("Shape of training data:", X_train.shape, y_train.shape)
print("Shape of testing data:", X_test.shape, y_test.shape)
```

```
Shape of training data: (800,) (800,)
Shape of testing data: (200,) (200,)
```

[40]:
```
clf = Pipeline([
    ('vectorizer_tri_grams', TfidfVectorizer()),
    ('naive_bayes', (MultinomialNB()))
])
```

[41]:
```
clf.fit(X_train, y_train)
```

[41]:
```
Pipeline(steps=[('vectorizer_tri_grams', TfidfVectorizer()),
                ('naive_bayes', MultinomialNB())])
```

[42]:
```
y_pred = clf.predict(X_test)
```

[43]:
```
print(accuracy_score(y_test, y_pred))
```

```
0.545
```

[44]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.11      0.20        35
           1       0.65      0.75      0.70        53
           2       0.49      0.60      0.54        57
           3       0.48      0.56      0.52        55

    accuracy                           0.55       200
   macro avg       0.61      0.51      0.49       200
weighted avg       0.58      0.55      0.52       200
```

[45]:
```
clf = Pipeline([
    ('vectorizer_tri_grams', TfidfVectorizer()),
    ('naive_bayes', (RandomForestClassifier()))
])
```

[46]:
```
clf.fit(X_train, y_train)
```

```
[46]: Pipeline(steps=[('vectorizer_tri_grams', TfidfVectorizer()),
                      ('naive_bayes', RandomForestClassifier())])
```

```
[47]: y_pred = clf.predict(X_test)
```

```
[48]: print(accuracy_score(y_test, y_pred))
```

```
0.51
```

```
[49]: print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.17      0.29        35
           1       0.44      0.87      0.59        53
           2       0.51      0.42      0.46        57
           3       0.60      0.47      0.53        55

    accuracy                           0.51       200
   macro avg       0.64      0.48      0.47       200
weighted avg       0.60      0.51      0.48       200
```

```
[52]: test_df = pd.read_csv('/content/twitter_validation.csv',
header=None) test_df.columns = ['id', 'source', 'Sentiment', 'Text']
# Assign columns as per␣
↪the original structure test_df =
test_df.rename(columns={'Sentiment': 'Label'})
test_df = test_df[['Text', 'Label']]
```

```
[53]: test_text = test_df['Text'][10]
print(f"{test_text} ===>
{test_df['Label'][10]}")
```

```
The professional dota 2 scene is fucking exploding and I completely
welcome it.

Get the garbage out. ===> Positive
```

```
[54]: test_text_processed = [preprocess(test_text)]
test_text_processed
```

```
[54]: ['professional dota 2 scene fuck explode completely welcome \n\n
garbage']
```

```
[55]: test_text = clf.predict(test_text_processed)
```

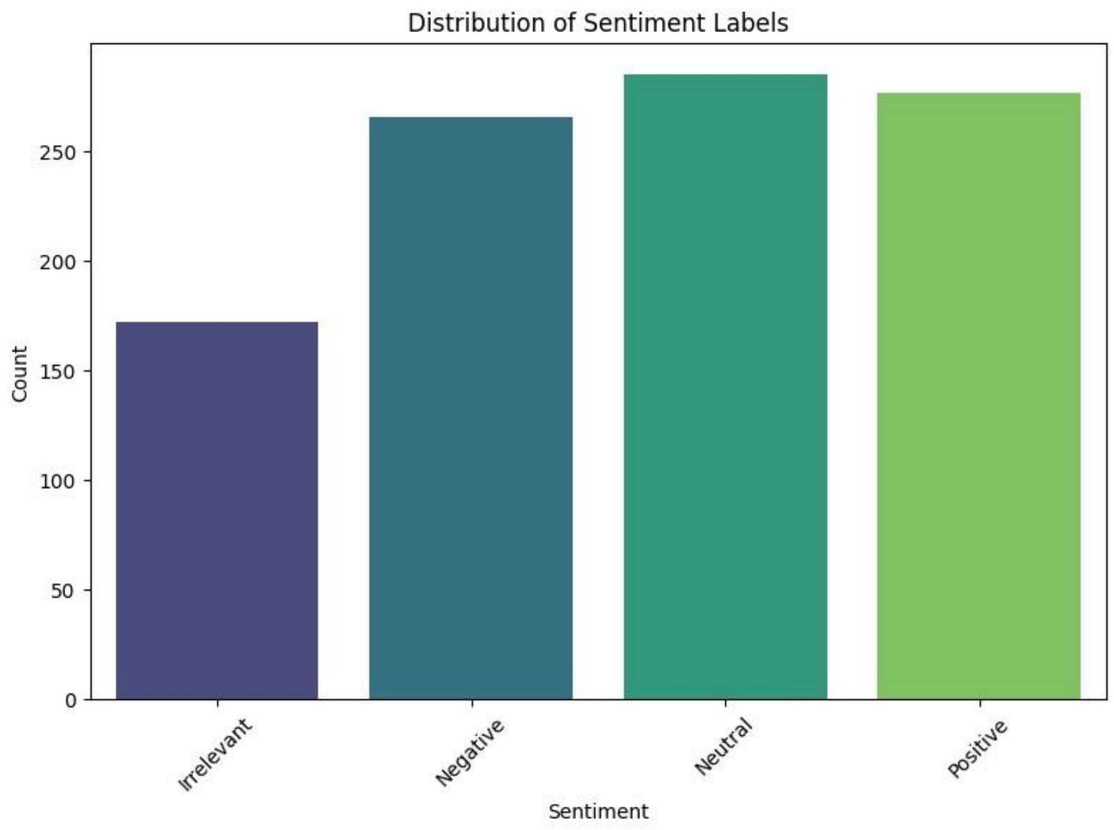
```
[56]: # Use the inverse transform of the LabelEncoder to get the original
class names classes = le_model.classes_
```

```
print(f"True Label: {test_df['Label'].iloc[10]}") # Using .iloc to
access by␣
 ↪position print(f'Predict Label:
{classes[test_text[0]]}')
```

```
True Label: Positive
Predict Label: Negative
```

[57]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Get the counts of each label
label_counts = df['Label'].value_counts().sort_index()

# Map encoded labels back to original class names for better readability
original_labels = le_model.inverse_transform(label_counts.index)

plt.figure(figsize=(8, 6))
sns.barplot(x=original_labels, y=label_counts.values, palette='viridis')
plt.title('Distribution of Sentiment Labels')
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-779907872.py:11: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

      sns.barplot(x=original_labels, y=label_counts.values,
                          palette='viridis')
```



Distribution of Sentiment Labels
Count
0
50
100
150
200
250
Irrelevant
Negative
Neutral
Positive
Sentiment