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Research Article

Quantitative Sentiment Analysis of Women's Safety Using Twitter Data: An NLP Approach

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ABSTRACT

In today's world of digitalization, social media platforms like Twitter serve as important outlets where people express their concerns and opinions on various societal issues including safety. Women's safety remains a significant concern, particularly in urban areas where incidents are often discussed publicly on social platforms. Despite the growing availability of such data there is a gap between analyzing social media sentiment and applying it to understand real-world safety issues. The issue lies in the underutilization of social media analytics for meaningful insights into public perceptions and potential policy interventions regarding women's safety. Twitter had 335.7 million monthly active users (MAU) in 2024, down 5.14% from 2023. There were 368.4 million users in 2022, the largest amount to date. Between 2018 and 2021, approximately 2% of all tweets originating from India contained elements of misogynistic language or sentiment. This research addresses that gap by conducting a comprehensive sentiment analysis of tweets related to women's safety identifying public sentiment patterns and highlighting the critical areas that require attention. Using NLP to process the data and to classify sentiments, this research paper will provide actionable insights. The paper is organized into several sections including a literature review, methodology, results and implications of Women Safety. Each section is designed to provide a comprehensive understanding of the research process from data collection to the implementation of the code and the interpretation of results. The findings from this analysis can support the development of real-time safety monitoring systems and addressing women's safety concerns more effectively.

Keywords: Sentiment analysis, women's safety, Twitter data, natural language processing, public perception.

1. INTRODUCTION

Harassment and violence including aggressive behaviors like staring and making comments are often seen as a normal part of city life though they are completely unacceptable. Studies conducted in various Indian cities have revealed that women frequently experience similar types of sexual harassment and catcalling from strangers [1]. A study across major metropolitan areas such as Delhi, Mumbai and Pune found that 60% of women [2] feel unsafe while commuting to work or using public transportation. Women have the right to move freely within the city [3] whether they are heading to educational institutions or other destinations. However, many women feel vulnerable in public spaces like malls or on their way to work due to unwanted attention body-shaming and harassment [4]. The lack of adequate safety measures and consequences for such behavior plays a key role in perpetuating this issue. There are cases where young girls are harassed by their neighbors [5] on their way to school instilling a deep sense of fear that can affect them for the rest of their lives. These experiences whether involving coercion or sexual harassment have long-lasting effects on victims.

Efforts to create safer cities should focus on women's right to move freely without the fear of violence or harassment rather than imposing societal restrictions on them [6]. It is the responsibility of society to prioritize women's protection and acknowledge that women and girls deserve to feel safe in their cities.

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In today's world Twitter has become a leading microblogging platform with over 100 million users [7] generating more than 500 million posts commonly referred as "tweets" daily. With such a large user base Twitter has attracted individuals who share their views and opinions on virtually every topic online making it a valuable source of information for various sectors like educational institutions, companies and organizations. On Twitter users express their thoughts and viewpoints through tweets. These posts are limited to 140 characters [8] encouraging users to condense their messages using abbreviations, slang, shorthand, emojis and more. Additionally, many people convey their ideas through the use of polysemy and sarcasm.

Despite the vast amount of data available on social media there is a significant gap in understanding how these sentiments translate into real-world safety concerns.

2. LITERATURE SURVEY

Table 1 : Literature Survey

Paper Title	Methodology	Key Findings	Research Gap
N. Mamgain, E. Mehta, A. Mittal and G. Bhatt, "Sentiment analysis of top colleges in India using Twitter data," 2016 *International Conference on Computational Techniques in Information and Communication Technologies (ICCTICT),* New Delhi, India, 2016, pp. 525-530, doi: 10.1109/ICCTICT.2016.7514636	Naive Bayes, SVM, ANN	AIIMS had highest positive sentiment.	Limited to specific colleges and not all perspectives represented
Karamouzas, D., Mademlis, I. & Pitas, I. Public opinion monitoring through collective semantic analysis of tweets. *Soc. Netw. Anal. Min.* **12**, 91 (2022). https://doi.org/10.1007/s13278-022-00922-8	Semantic descriptor with NLP algorithms	Automated public opinion monitoring through semantic analysis	Limited focus on individual salient dates for public opinion.
Soo-Min Kim and Eduard Hovy. 2004. Determining the Sentiment of Opinions. In *COLING 2004: Proceedings of the 20th International Conference on Computational Linguistics*, pages 1367–1373, Geneva, Switzerland. COLING.	Quadruple-based model (Topic, Holder, Claim, Sentiment)	Basic sentiment polarity model effective	Struggles with multiple or implicit opinions
Apoorv Agarwal, Fadi Biadsy and Kathleen R. McKeown. 2009. Contextual Phrase-Level Polarity Analysis Using Lexical Affect Scoring and Syntactic N-Grams. In Proceedings of the *12th Conference of the European Chapter of the ACL (EACL 2009),* pages 24–32, Athens, Greece. Association for Computational Linguistics.	Lexical scoring, syntactic n-grams	Improved phrase-level sentiment detection	Dependent on predefined dictionaries and also there is a difficulty handling informal language
Barbosa, L., & Feng, J. (2010). Robust Sentiment Detection on Twitter from Biased and Noisy Data. *International Conference on Computational Linguistics*.	Feature extraction and abstract representation	Effective even with noisy and biased data	Generalizability issues due to noisy data
Michael Gamon. 2004. Sentiment classification on customer feedback data: noisy data, large feature vectors and the role of linguistic analysis. In COLING 2004: *Proceedings of the 20th International Conference on Computational Linguistics, pages 841–847,* Geneva, Switzerland. COLING.	SVM with large feature vectors and linguistic analysis features	High classification accuracy achieved with feature reduction and deep linguistic analysis	Feedback data often noisy and unstructured and also requiring heavy pre-processing

Bhumika Gupta, Monika Negi, Kanika Vishwakarma, Goldi Rawat, Priyanka Badhani .Study of Twitter Sentiment Analysis using Machine Learning Algorithms on Python. *International Journal of Computer Applications*. 165, 9 (May 2017), 29-34. 10.5120/ijca2017914022	Python-based ML approach	Challenges due to tweet format and informal language	Difficulty processing short-length tweets with slang and abbreviations
Rodríguez-Sánchez, F., Carrillo-de-Albornoz, J., & Plaza, L. (2020). Automatic Classification of Sexism in Social Networks: An Empirical Study on Twitter Data. *IEEE Access, 8*, 219563-219576.	Logistic Regression, Support Vector Machine, Random Forest. Deep learning methods: CNNs, LSTMs, Bi-LSTM, mBERT.	Sexism detected in various forms on social networks and how Deep learning models effectively classify different sexism types.	Models still make mistakes in detecting sexism. There is a need for deeper analysis of model errors.

3. RESEARCH OJECTIVE

- To analyze and assess the sentiment of tweets related to women's safety categorizing them as positive, negative or neutral.
- To identify trends and patterns in public sentiment regarding women's safety over time particularly in response to specific events or campaigns.
- To highlight key issues and concerns raised in tweets regarding women's safety providing a deeper understanding of societal attitudes and perceptions.
- To contribute to enhancing public awareness and discussion around women's safety by providing insights derived from real-time social media data.
- To develop a user-friendly tool or application that allows stakeholders to easily access and analyze sentiments regarding women's safety in real time.

4. METHODOLOGY

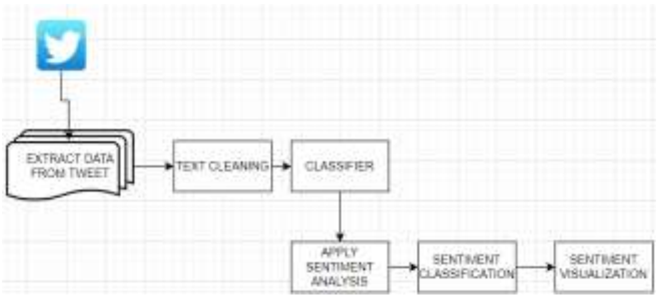

Fig. 1: Block Diagram

4.1. Data Collection: Gather tweets related to women's safety using Twitter API or Kaggle.

4.2. Data Preprocessing: Clean the collected tweets:

4.2.1. Remove duplicates

4.2.2. Remove null and incomplete data

4.2.3. Eliminate special characters and unnecessary information

4.3. Sentiment Analysis with TextBlob: For each tweet apply TextBlob to calculate the sentiment polarity

4.4. Categorize Sentiment: Categorize the sentiment scores:

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4.4.1. Positive (score > 0)

4.4.2. Neutral (score == 0)

4.4.3. Negative (score < 0)

4.5. **Data Visualization:** Visualize the results using charts or graphs:

4.5.1. Pie charts showing the proportion of positive, neutral and negative sentiments.

This research adopts a quantitative approach. It involves data collection from Twitter preprocessing and cleaning of the dataset followed by sentiment analysis.

5. TOOLS & TECHNOLOGY

The tools and technologies used in this project include:

- **Python** for programming.
- **TextBlob** for sentiment analysis.
- **Pandas** for data manipulation and cleaning.
- **Tkinter** for developing the GUI.
- **Matplotlib** for graphical representation of results.

6. RULE BASED APPROACH

A rule-based approach refers to a method of text analysis that relies on predefined rules or heuristics to interpret and analyze data [19]. Instead of using statistical or machine learning techniques to learn patterns from data rule-based systems use a set of explicit rules defined by experts to derive insights from text.

Key Characteristics of Rule-Based Approaches

- The analysis is driven by a set of explicit rules created based on domain knowledge. For example, a rule might state that if a word like "happy" appears in a sentence the sentiment is classified as positive.
- Rule-based systems often utilize lexicons dictionaries of words with associated sentiment scores or categories. These lexicons help determine the sentiment of a text based on the words it contains.
- The decision-making process is transparent because the rules are clearly defined and can be easily understood and interpreted by humans.
- Rule-based approaches generally require less data for setup compared to machine learning models which often need large labelled datasets to train effectively.
- They tend to be faster than machine learning models because they don’t involve the computational overhead of training and learning from data.

Advantages:

- Easy to implement and understand.
- Does not require large datasets or complex algorithms.
- Results can be easily interpreted and communicated.

6.1 TEXTBLOB

TextBlob was likely chosen for this project because of its simplicity and ease of use for sentiment analysis [15]. Here are a few reasons why only TextBlob might have been used and not other rule-based approaches:

6.1.1 Ease of Implementation:

- TextBlob is a high-level library that simplifies many NLP tasks like sentiment analysis, part-of-speech tagging and translation with minimal coding effort.
- It provides easy access to sentiment polarity (positive, negative or neutral) which fits the project's goal without needing complex setup or training.

6.1.2 Readily Available Sentiment Analysis:

- TextBlob comes with a built-in sentiment analysis tool that works out of the box using a lexicon-based approach. This makes it fast and convenient for projects where speed is more important than accuracy or

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customization.

6.1.3 Sufficient for Small-Scale Projects:

- For simple sentiment analysis tasks (like classifying tweets as positive, neutral or negative), TextBlob offers sufficient accuracy and performance without needing complex processing.

6.1.4 Minimal Computational Resources:

- Unlike some other approaches (like ML models or deep learning techniques), TextBlob doesn't require large datasets or heavy computational resources. It runs efficiently even on modest hardware.

Why Not Other Rule-Based Approaches?

- ***VADER (Valence Aware Dictionary and sEntiment Reasoner):*** Another popular rule-based sentiment analyzer that is specifically tuned for social media data like tweets. However it might not have been chosen if simplicity and basic sentiment detection were enough for the project.
- ***SentiWordNet:*** This lexicon-based method provides fine-grained sentiment scores. However, it can be more complex to integrate and may not offer substantial benefits over TextBlob for basic sentiment analysis tasks.

Ultimately, TextBlob was likely chosen because it balances ease of use and efficiency for a project focused on quickly analysing sentiments in Twitter data without requiring the training or tuning of models. If higher accuracy or customization is needed, additional tools or more advanced models like VADER or machine learning models could be incorporated.

EXAMPLE OF TEXTBLOB

```
from textblob import TextBlob
import pandas as pd
import matplotlib.pyplot as plt

sentences = [
    "I love programming in Python!",
    "The weather today is terrible."
]
polarities = []
subjectivities = []
sentiment_labels = []
for sentence in sentences:
    blob = TextBlob(sentence)
    polarities.append(blob.sentiment.polarity)
    subjectivities.append(blob.sentiment.subjectivity)
    if blob.sentiment.polarity > 0:
        sentiment_labels.append('Positive')
    elif blob.sentiment.polarity < 0:
        sentiment_labels.append('Negative')
    else:
        sentiment_labels.append('Neutral')
results_df = pd.DataFrame({
    'Sentence': sentences,
    'Polarity': polarities,
    'Subjectivity': subjectivities,
    'Sentiment Label': sentiment_labels
```

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```
})
print(results_df)
plt.figure(figsize=(10, 5))
plt.bar(results_df['Sentence'], results_df['Polarity'],
alpha=0.6, label='Polarity', color='b')
plt.bar(results_df['Sentence'], results_df['Subjectivity'],
alpha=0.6, label='Subjectivity', color='g')
plt.xlabel('Sentences')
plt.ylabel('Scores')
splt.title('Sentiment Analysis of Sentences')
plt.legend()
plt.grid()
plt.show()
```

Output:

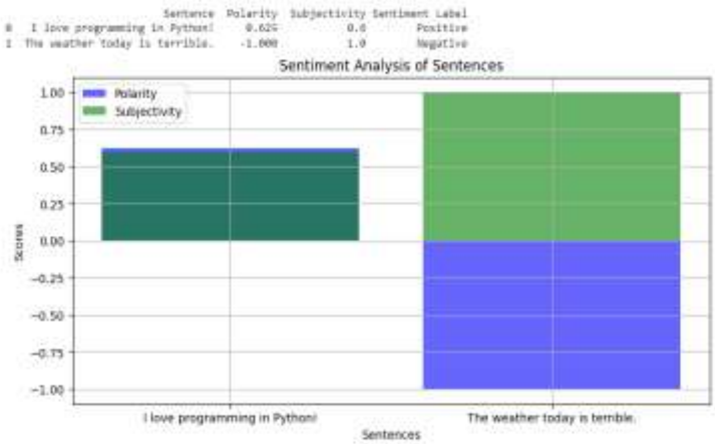

Fig. 2: Output of Example Code of TextBlob

7. INPUT CODE

MAIN PROGRAM CODE

```
def run_algorithm(text_widget):
  global positive_count, negative_count, neutral_count
  text_data = text_widget.get("1.0", "end-1c")
  corpus = text_data.split("\n")
  sentiment_scores = []
  for tweet in corpus:
    analysis = TextBlob(tweet)
sentiment_scores.append(analysis.sentiment.polarity)
  positive_count = sum(score > 0 for score in sentiment_scores)
  negative_count = sum(score < 0 for score in sentiment_scores)
```

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```
    neutral_count = sum(score == 0 for score in sentiment_scores)
    analysis_result = f"Positive Tweets: {positive_count}\n"
    analysis_result += f"Negative Tweets: {negative_count}\n"
    analysis_result += f"Neutral Tweets: {neutral_count}\n"
    text_widget.delete("1.0", "end")
    text_widget.insert("1.0", analysis_result)
def run_algorithm(text_widget):
    global positive_count, negative_count, neutral_count
    text_data = text_widget.get("1.0", "end-1c")
    corpus = text_data.split("\n")
    sentiment_scores = []
    for tweet in corpus:
        analysis = TextBlob(tweet)
        sentiment_scores.append(analysis.sentiment.polarity)
    positive_count = sum(score > 0 for score in sentiment_scores)
plt.xlabel('Sentences')
plt.ylabel('Scores')
splt.title('Sentiment Analysis of Sentences')
plt.legend()
plt.grid()
plt.show()
```

EXPLAINATION:

- **Input:** The function receives the text_widget which contains the cleaned tweets.
- **Data Retrieval:** It retrieves the content from the text_widget and splits it into individual tweets using the newline character as a delimiter.
- **Sentiment Analysis:** For each tweet, it creates a TextBlob object and gets the polarity score. The polarity score ranges from -1 (very negative) to +1 (very positive), with 0 being neutral.
- **Counting Sentiments:** It calculates the sum of positive, negative and neutral tweets by counting the polarity scores.
- **Display Results:** The results are formatted as a string and displayed in the text_widget

ALGORITHM

```
Start
Initialize the GUI (using Tkinter):
    Create a window
    Create labels, textboxes and buttons
```

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```
Load Dataset (when "Upload and Read Tweets Data" is clicked):
    Open file dialog to select CSV file
    Load CSV data into a DataFrame using pandas
    Display the dataset in the textbox
Clean Tweets (when "Tweet cleaning" is clicked):
    Read the data from the textbox
    Remove duplicate tweets
    Remove null values and incomplete data ("...")
    Remove special characters
    Sort cleaned tweets alphabetically
    Update the textbox with cleaned tweets
Run Sentiment Analysis (when "Run machine learning algorithm" is clicked):
    Read the cleaned tweets from the textbox
    Initialize positive, negative and neutral tweet counters
    For each tweet:
        Use TextBlob to analyze the sentiment polarity
        If polarity > 0:
            Increment positive counter
        Else if polarity < 0:
            Increment negative counter
        Else:
            Increment neutral counter
    Display the number of positive, negative and neutral tweets
```

1. GUI Setup:

Step 1.1: Initialize the GUI using Tkinter which creates the main window.

Step 1.2: Set up labels, text areas and buttons.

Step 1.3: Create fonts and styling to enhance the user interface.

2. Load Dataset:

Step 2.1: When the "Upload and Read Tweets Data" button is clicked, open a file dialog to select a CSV file.

Step 2.2: Use pandas to load the selected CSV file into a DataFrame.

Step 2.3: Display the dataset inside the textbox widget.

3. Clean Tweets:

Step 3.1: Read the tweets from the textbox after uploading.

Step 3.2: Remove duplicate tweets.

Step 3.3: Remove null values, incomplete data (like "...") and special characters.

Step 3.4: Sort the cleaned tweets in ascending order and update the textbox.

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4. Sentiment Analysis (Run Algorithm):

Step 4.1: Retrieve the cleaned tweets from the textbox.

Step 4.2: Loop through each tweet:

- **Step 4.2.1:** For each tweet a TextBlob object to analyze its sentiment.
- **Step 4.2.2:** Extract the **polarity score** (ranges from -1 to +1).

Polarity > 0: Positive sentiment.

Polarity < 0: Negative sentiment.

Polarity = 0: Neutral sentiment.

Step 4.3: Calculate the total number of tweets categorised as positive, negative and neutral.

Step 4.4: Display the sentiment analysis outcomes (sum of positive, negative and neutral tweets) in the textbox.

5. Visualize Results (Graph Analysis):

Step 5.1: Retrieve the sentiment analysis

Step 5.2: Calculate the percentage of each sentiment type

Step 5.3: Plot a pie chart using matplotlib to visualize the distribution of sentiment.

Step 5.4: Show the chart to the user.

8. RESULTS & DISCUSSION

Fig 3. Home Window

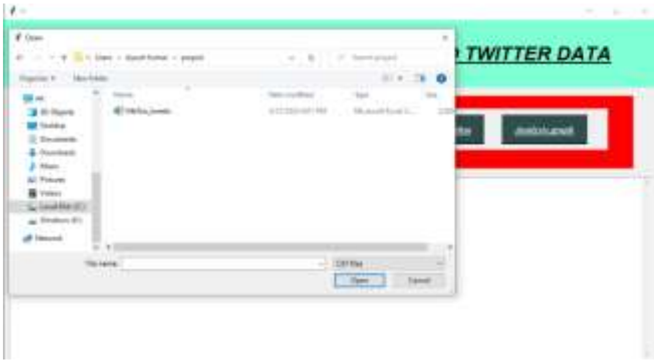

Fig 4: Selecting the Dataset

With the help of upload and tweet button we select the dataset and upload it in application.

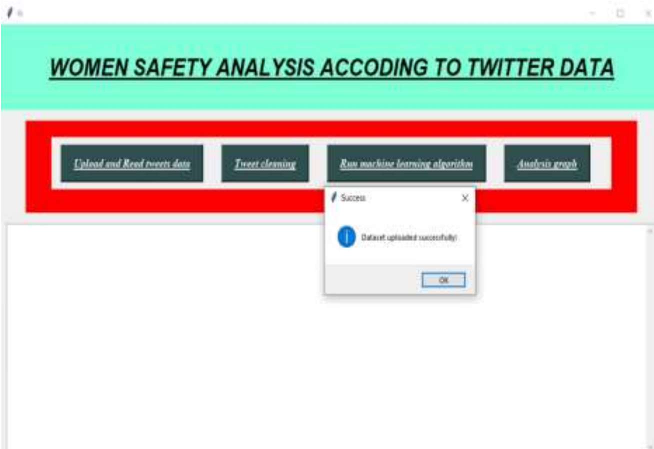

Fig 5: Uploaded Successfully

When we select the data file and upload it. Then it shows a message “Dataset Uploaded Successfully. If the data is not uploaded the it shows a message “Dataset Uploaded Failed”.

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Fig 6: Upload & Read Data

After the loading data, We read the data set which is uploaded

Fig 7: Tweet Cleaning

After upload and read the data, We clean the tweet. Our data set has lots of tweets some are incomplete tweets, duplicate, empty, undefined or some with the special character. So we'll go for tweet cleaning.

Fig 8: Run Algorithm

After the tweet cleaning, We apply the Machine learning algorithm for sentiment analysis on the tweets.

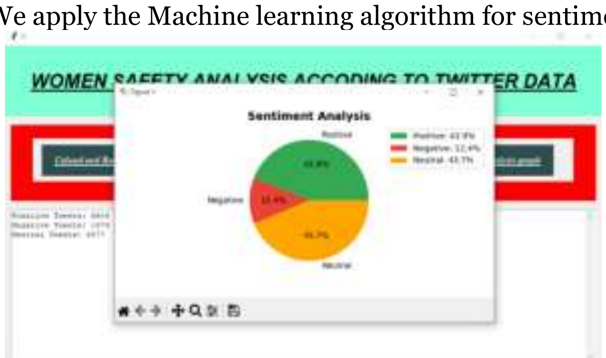

Fig 9: Tweet Analysis

After the machine learning algorithm we get our analysis result in the form of graph (basically in Pie chart form)

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9. IMPLICATIONS OF WOMEN SAFETY

This research has significant implications for understanding women's safety by analyzing social media discussions particularly on Twitter. The sentiment analysis conducted on real-time tweets provides insights into public perceptions, concerns and experiences related to women's safety. By identifying patterns of positive, negative and neutral sentiments stakeholders such as government bodies, NGOs and law enforcement can gauge areas of concern understand the emotional responses of the public and devise more targeted safety initiatives. Additionally, the sentiment trends can help predict potential safety issues highlighting regions or incidents that need immediate attention thus improving preventive measures.

10. LIMITATIONS

- The study used only the TextBlob library for sentiment analysis which may limit the accuracy compared to more advanced machine learning-based techniques such as BERT or VADER. TextBlob is a rule-based system and might not handle sarcasm or nuanced sentiment as effectively.
- The data extracted from Twitter may contain noise including irrelevant tweets or misleading information which could affect the sentiment analysis results. Additionally, due to privacy restrictions we could not access private or deleted tweets which might provide further insights.
- Sentiment Analysis emphasizes the positive or negative nature of terms and phrases but may fail to capture the full context of the discussions around women's safety. For instance, a negative sentiment may not always indicate an unsafe situation but rather frustration with policies.
- The research did not utilize geo-tagged data limiting the ability to analyze tweets based on specific locations where women's safety might be a critical issue.
- The dataset was limited to a specific period and number of tweets. Larger datasets and longer-term analysis might offer a more comprehensive view of the issue.

11. CONCLUSION

In conclusion, the research highlights the importance of social media as a tool for understanding public sentiment about women's safety. By using TextBlob for sentiment analysis, the project reveals valuable insights into how women’s safety is discussed online uncovering areas of concern that might otherwise go unnoticed. The research emphasizes the potential for real-time monitoring of social discourse allowing stakeholders to identify emerging threats or trends related to safety issues. With improvements such as incorporating geo-tagged data and advanced sentiment analysis techniques future work can provide even more comprehensive insights. The project's results serve as a foundation for stakeholders whether policymakers, organizations or the public to take action based on data-driven insights. This analysis not only informs better decision-making but also underscores the role of digital platforms in creating safer environments. As the online world grows research in this domain becomes essential for proactively addressing safety concerns and fostering greater trust in digital spaces for women.

12. FUTURE RESEARCH DIRECTIONS

- **Incorporating Advanced Machine Learning Models:** Future studies can integrate machine learning-based sentiment analysis models like BERT, VADER or LSTM which have higher accuracy in understanding sentiment nuances including sarcasm, irony and deeper context.
- **Expanding Data Sources:** Including data from other social media platforms like Facebook, Instagram and Reddit could provide a broader view of discussions on women’s safety.
- **Location-Based Analysis**: Geo-tagged data can provide insights into specific regions where women's safety is a bigger concern leading to more localized safety initiatives.
- **Longitudinal Analysis:** Conducting sentiment analysis over an extended period can identify trends and shifts in public sentiment enabling a better understanding of how issues related to women’s safety evolve over time.
- **Incorporating Multilingual Data:** Since Twitter is used globally analyzing tweets in multiple languages can offer a more inclusive view of the public's concerns about women’s safety.
- **Combining Sentiment with Event Data:** Future research could combine sentiment analysis with actual crime data to establish correlations between public sentiment and real-world safety incidents.

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