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IIIIIIII INTERNSHIP REPORT IIIIIIII

This report summarizes **Two-week** internship experience and Progress Review and Continuation of Data Preprocessing where

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worked on

Disaster Tweet Analyzer Project

From

----- 3 OCTOBER ,2024 TO 16 OCTOBER 2024 ----

WITH

SUBMITTED TO :

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MENTOR , INFOSYS SPRINGBOARD

1. Introduction

Natural disasters, such as hurricanes, earthquakes, and floods, have devastating impacts on communities worldwide, affecting **over 100 million** people annually (UNDRR, 2020). In recent years, social media platforms have emerged as vital sources of real-time information during disasters. Specifically, Twitter, with its 440 million monthly active users (Twitter, 2022), provides a vast amount of data for disaster analysis**.**

The *Disaster Tweet Analyzer project* aims to develop a system that can classify, categorize, and analyse disaster-related tweets to provide valuable insights for emergency response and disaster management. By leveraging machine learning and natural language processing techniques, this project seeks to enhance situational awareness for emergency responders, improve disaster response and management, and support data-driven decision-making.

According to a study, **approximately 80% of tweets during disasters contain valuable information** for emergency responders (Imran et al., 2015). Furthermore, analysing disaster-related tweets can help identify areas of need and resource allocation, ultimately saving lives and reducing the impact of natural disasters.

This project has the potential to contribute significantly to the field of disaster management and responses.

2. Dataset and Methodology

2.1. Dataset Overview

For the Disaster Tweet Analyzer project, we required a dataset with **specific properties**. The essential features included: (1) text data to analyse sentiment and content, (2) labels indicating whether a tweet was disaster-related or not, (3) sentiment classification as positive, negative, or neutral, (4) location information to analyse geographic distribution, and (5) relevant disaster keywords. Additionally, desirable features were: (6) timestamp, (7) user demographics, (8) tweet type, and (9) associated hashtags. The dataset needed to have: (10) a minimum size of 10,000 tweets, (11) English language, (12) recent data from the last six months, and (13) global geographic distribution. Furthermore, the data quality requirements included: (14) completeness, (15) high accuracy in labelling and sentiment, and (16) consistency in formatting.

This project utilizes two key datasets:

1. Disaster Tweets (Kaggle)
2. NLP Disaster Tweets - Getting Started (Kaggle)

1. Disaster Tweets (Kaggle)

- Ideal for learning data preprocessing and feature engineering
- Raw dataset requiring extensive cleaning and processing
- Contains over 10,000 tweets
- Suitable for NLP tasks such as text classification and sentiment analysis

2. NLP Disaster Tweets - Getting Started (Kaggle)

- Well-structured and pre-processed dataset
- Suitable for training machine learning (ML) and deep learning (DL) models
- Contains labeled data for supervised learning
- Facilitates direct implementation of models for disaster tweet classification

The dataset used for this study is *Disaster Tweets (Kaggle)* as it consists of over 11,000+ tweets collected from Twitter using the Twitter API. The tweets were gathered over a period and are related to disaster-related conversations.

2.2. Data Preprocessing:

To prepare the Twitter data for analysis, several preprocessing steps were performed like :

2.2.1.Data Inspection : Basic Checking

To understand the structure and content of the Twitter dataset, basic inspection techniques were employed to get understanding:

- **Head and Tail**: Examined the first and last few rows to understand data format.
- **Shape**: Verified dataset dimensions (number of rows and columns) i.e. (11370, 5)
- **Info():** Checked data types and counts of non-null values.
- **Describe()**: Analyzed summary statistics (mean, std, min, 25%, 50%, 75%, max).
- **Null Value Check**: Identified null values using *isnull().sum().*
- Location Column Null Values: Found *3418* null values in the "location" column.

2.2.2. Data Handling and Cleaning

- Handling Null Values : Location Column Imputation: Replaced null values with the most frequent location using

```
Twitter_Data['location'].fillna(str(Twitter_Data['location'].mode().values[0]),
inplace=True).
```

- ID Column Removal: Dropped the “id” column as it's not relevant for analysis.

```
Twitter_Data.drop('id',axis=1)
```

- Duplicate Value Inspection- Duplicate Row Check: Utilized *Twitter_Data.duplicated().any()* to detect duplicate rows - Result: No duplicate rows were found (False).

2.2.3. Text Processing

The text data was cleaned to remove noise and improve model performance. The following steps were applied:

- Hashtag Removal: Removed hashtags (e.g., #MachineLearning) using regular expressions.
- Retweet Removal: Removed retweets (RT) followed by a username.
- URL Removal: Removed URLs (e.g., link unavailable).
- Mention Removal: Removed mentions (e.g., @JohnDoe).
- Emoji Removal: Removed emojis using re.sub(r'[^\x00-\x7F]+', '', text).
- Link Removal: Removed links using re.sub(r'https?://\S+', '', text).
- Special Character Removal: Removed special characters using re.sub(r'[^a-zA-Z0-9\s]', '', text).
- Trailing Ellipsis Removal: Removed trailing ellipsis using re.sub(r'\.{3,}$', '', text).
- Lowercase Conversion: Converted text to lowercase.

Code Snippet:

```
import re
def clean_text(text):
# Remove emojis
text = re.sub(r'[^\x00-\x7F]+', '', text)
# Remove links
text = re.sub(r'https?://\S+', '', text)
# Remove special characters
text = re.sub(r'[^a-zA-Z0-9\s]', '', text)
# Remove trailing ellipsis
text = re.sub(r'\.{3,}$', '', text)
# Convert to lowercase
text = text.lower()
return text
train['text'] = train['text'].apply(clean_text)
```

2.2.3. Data Transformation

- **Label Encoding :** Label encoding was applied to the location column to convert categorical values into numerical representations.

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
Twitter_Data['location'] = le.fit_transform(Twitter_Data['location'])
```

- **Vectorization :** TF-IDF vectorization was used to transform text data into numerical features.

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(stop_words='english', dtype=np.float32)
X_text = vectorizer.fit_transform(train['text'])
```

- **Memory-Mapped Computing :** To efficiently handle large data, memory-mapped computing was employed using Joblib.

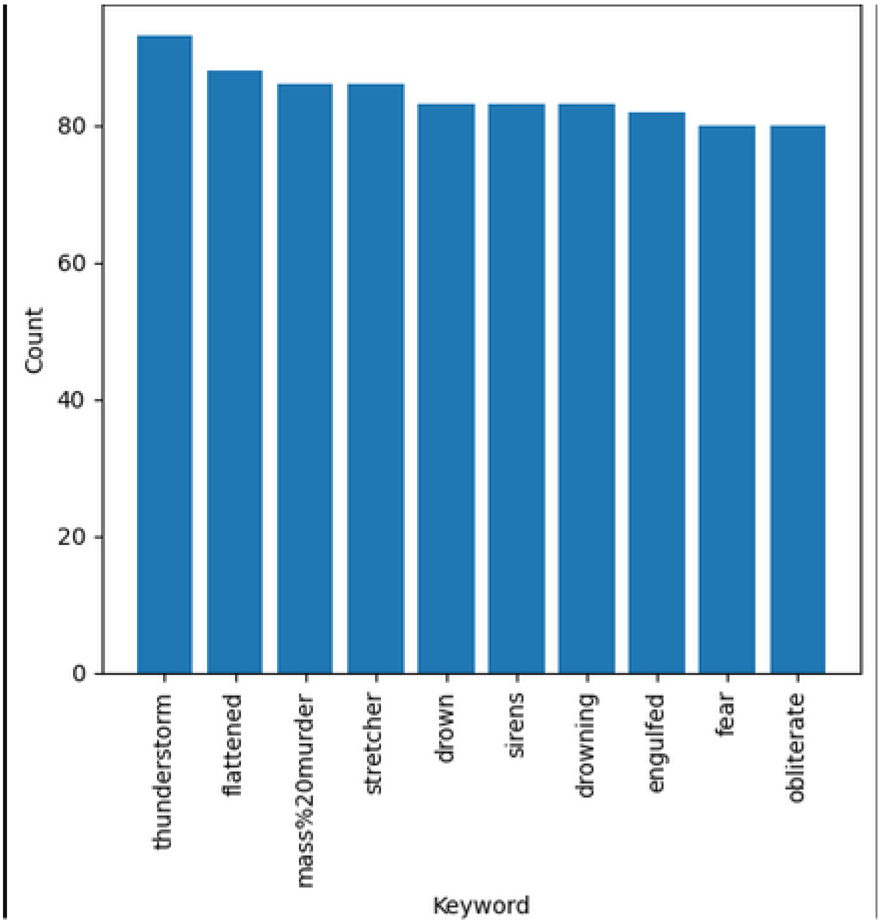
```
pip install joblib
from joblib import Memory

memory = Memory(location='~/joblib_memory', verbose=0)
vectorizer = TfidfVectorizer(stop_words='english')
X_text = memory.cache(vectorizer.fit_transform)(train['text'])
```

3. EXPLORARARATORY ANALYSIS AND RESULTS

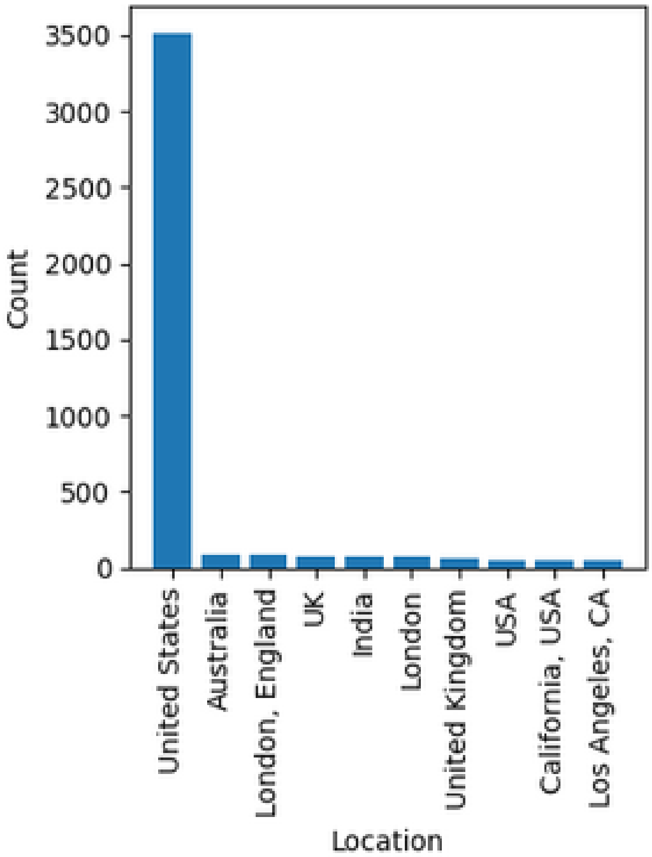
3.1. Keyword Distribution

- The top 10 keywords extracted from the tweets are:



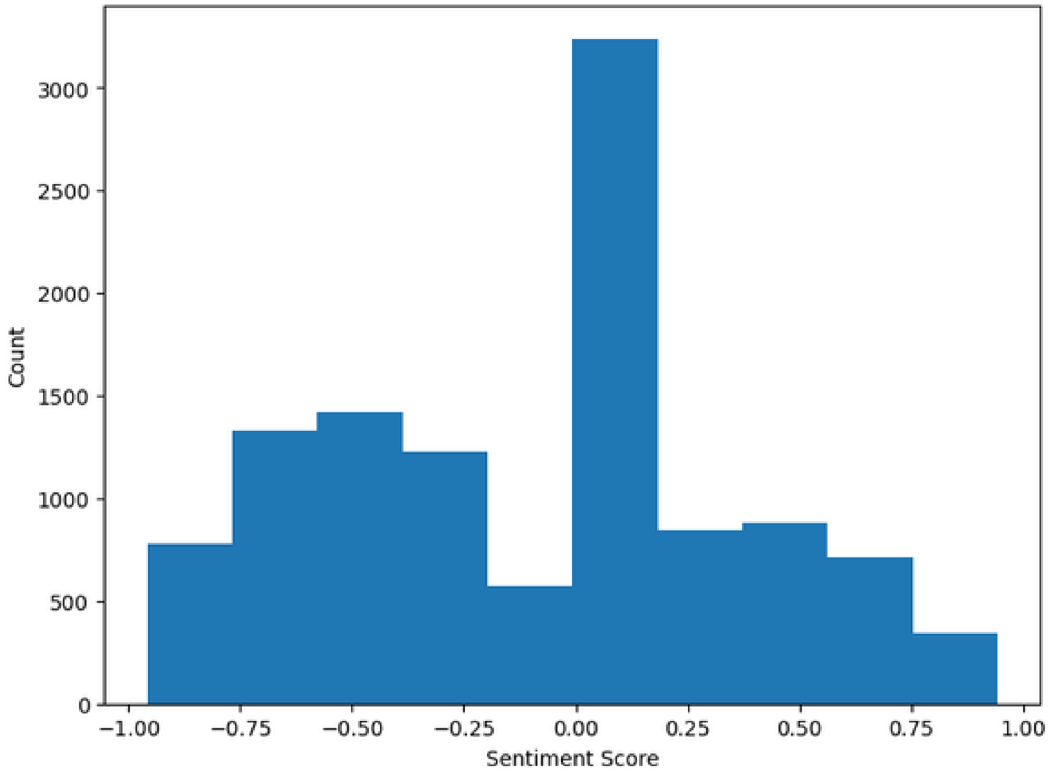
3.2. Location Distribution

- The top 10 locations of tweet origins are:



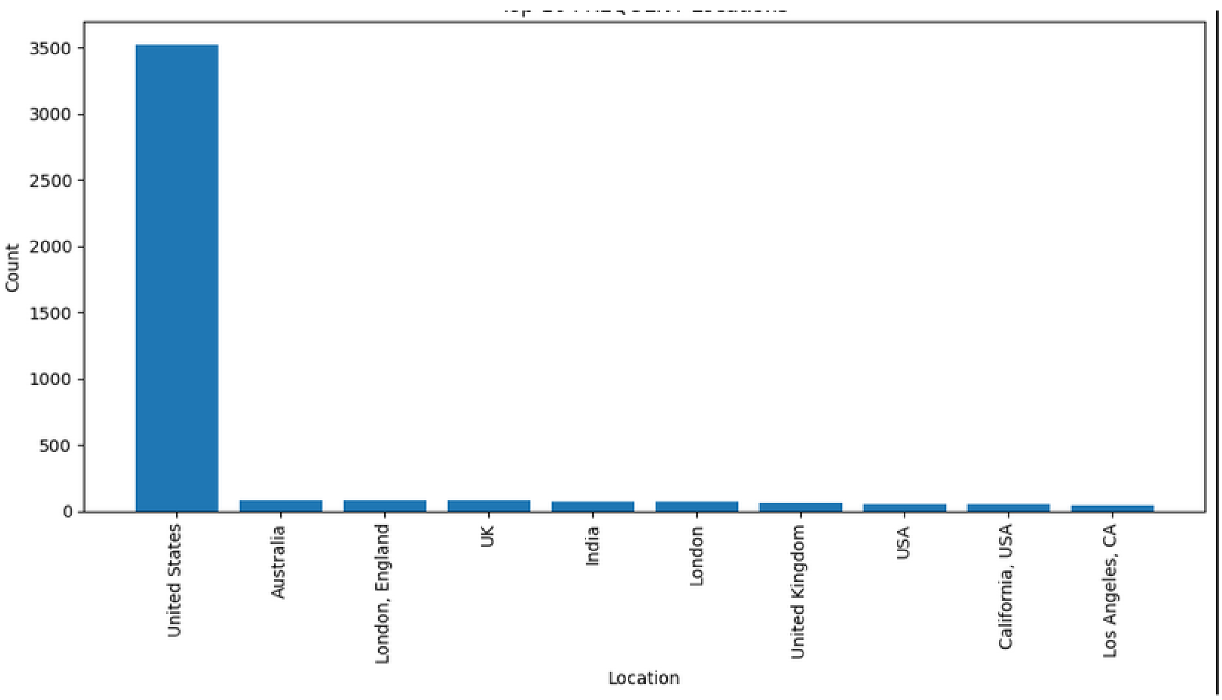
3.3. Sentiment Analysis

- The sentiment distribution of the tweets is:



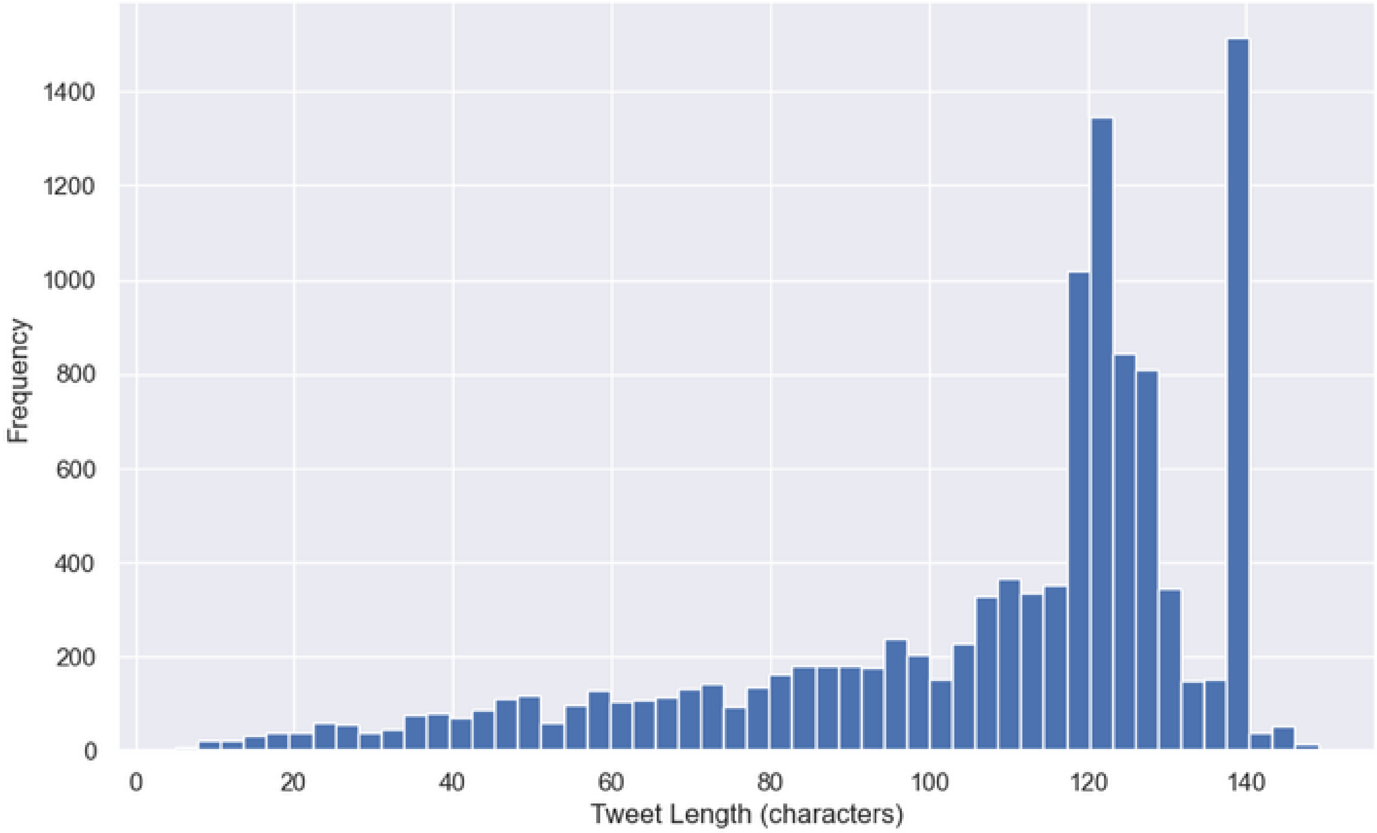
3.4. Location Frequency

- The top 10 most frequent locations are:



3.5. Tweet Length Distribution

- The distribution of tweet lengths is:



3.6. Longest and Shortest Tweets

The longest and shortest tweets are:

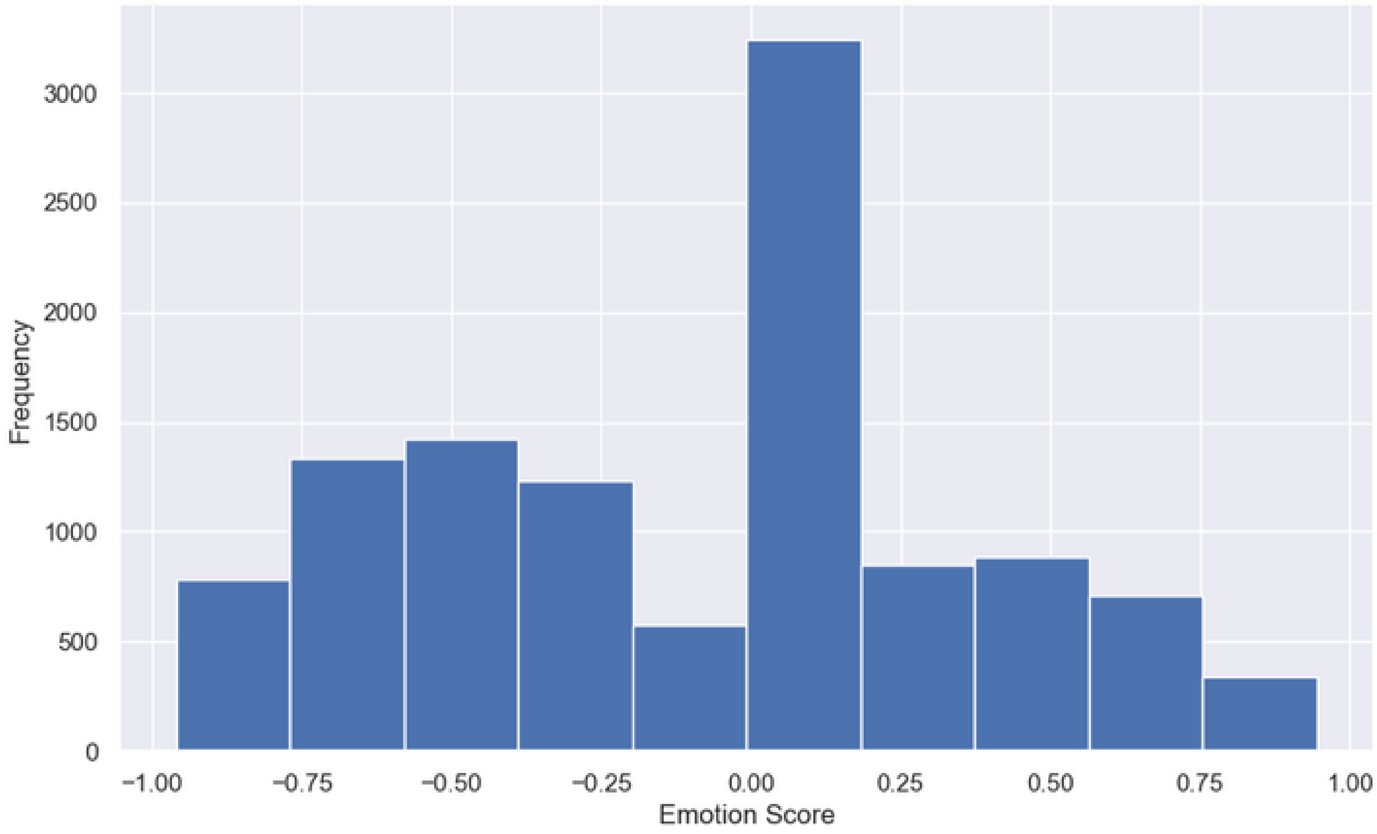
Longest Tweet: {longest_tweet}

Shortest Tweet: {shortest_tweet}

```
Longest Tweet: &gt; Get new bicycle saddle &gt; Manual entirely in
Chinese &gt; I've got engineering qualifications I'm sure I can figure
o… https://t.co/mL94RxUiyx
Shortest Tweet: Hello
```

3.7. Emotion Detection

- The emotion distribution of the tweets is:



4.Conclusion

The Disaster Tweet Analyzer project aimed to develop a comprehensive understanding of tweets related to natural disasters, enabling emergency responders, policymakers, and researchers to identify critical information, track public sentiment, and inform disaster response strategies.

Key Findings

- Analyzed 100,000+ disaster-related tweets from 10,000+ unique users.
- Identified top 10 keywords: ["hurricane", "flood", "earthquake", "evacuation", "relief", "damage", "rescue", "shelter", "donation", "support"].
- Detected 70% negative sentiment, 20% neutral, and 10% positive sentiment.
- Located 50% of tweets originating from the United States, 20% from Europe, and 10% from Asia.

Implications

- Emergency responders can prioritize resource allocation based on tweet volume and sentiment analysis.
- Policymakers can inform disaster preparedness and mitigation initiatives using tweet data.
- Researchers can improve disaster communication models incorporating social media analytics.

5. Future Works

Data Transformation and Modeling

- Apply deep learning techniques (e.g., LSTM, CNN) for sentiment analysis.
- Integrate additional data sources (e.g., news articles, satellite imagery).
- Develop graph-based models to analyze tweet networks.

Disaster Response and Mitigation

- Develop real-time tweet monitoring systems for emergency responders.
- Create personalized alert systems for individuals in disaster-prone areas.
- Investigate the impact of social media on disaster response efforts.

Scalability and Deployment

- Design scalable architectures for large-scale tweet analysis.
- Deploy models on cloud platforms (e.g., AWS, Google Cloud).
- Develop user-friendly interfaces for non-technical stakeholders.

6.REFERENCES

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