Disaster Tweet Analyzer: Natural Language Processing for Crisis Communication

An Executive Summery

Submitted in complete fulfilment of the requirements of 2-month internship

Internship Duration:

3 October 2024 to 29 November 2024

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ABSTRACT

The **Disaster Tweet Analyzer** project explores the integration of **Artificial Intelligence (AI)** and **Natural Language Processing (NLP)** to classify tweets as disaster-related or non-disaster-related, addressing the growing reliance on social media for real-time disaster communication. By utilizing a dataset of over **11,000 labeled tweets** from the Kaggle Disaster Tweets dataset, the project focuses on preprocessing text data, extracting relevant features, and developing a machine learning model for accurate classification. **Logistic Regression** was selected as the primary classifier, offering a balance between computational efficiency and accuracy. Additionally, a merged dataset with an enhanced target column was incorporated to improve classification precision.

The project achieved significant milestones, including the development of a high-performing model with strong evaluation metrics such as precision, recall, F1-score, and accuracy, demonstrating the potential of AI-powered solutions in disaster management. The implementation of **SMOTE** addressed class imbalance issues, enhancing model reliability. Moreover, the project features a **user-friendly web application** that delivers real-time insights on disaster classifications, sentiment analysis, and auxiliary information, such as disaster location and type. To further improve user engagement, the system integrates a chatbot, **Tarini**, capable of providing detailed, AI-driven disaster-related insights.

Despite its accomplishments, the project faced challenges, particularly the inability to fully utilize **Twitter's API** for real-time tweet analysis due to access restrictions. This limitation presents an opportunity for future enhancement, alongside the implementation of a tweet-flagging system for reporting and collaboration. The proposed future directions include incorporating real-time tweet analysis, improving the system's ability to verify tweet authenticity, extracting granular location details, and expanding the model to classify multilingual tweets. Additionally, transitioning the system into a **Chrome extension** could enable seamless social media integration and immediate disaster insights.

This project underscores the transformative potential of AI and NLP in disaster response and management by demonstrating the feasibility of filtering and analyzing social media data for crisis communication. With future advancements and the integration of emerging technologies, the **Disaster Tweet Analyzer** could evolve into a comprehensive tool for effective disaster preparedness and mitigation.

Keywords: Disaster Tweet Classification, Natural Language Processing, Machine Learning, Logistic Regression, Social Media Analysis.

INTRODUCTION

Introduction

Disasters, whether natural or man-made, have profound and far-reaching effects, disrupting lives, economies, and ecosystems. In these critical moments, timely and accurate information becomes essential for effective response and resource allocation. Social media platforms like Twitter have emerged as crucial tools during disasters, offering real-time insights through user-generated content. Tweets often serve as primary indicators of disaster events, providing valuable information about their location, type, and immediate impacts [1][2]. However, the unstructured and vast nature of social media data poses challenges in identifying relevant and reliable information swiftly.

In light of this, disaster tweet analysis has become a promising field. Machine Learning (ML) and Natural Language Processing (NLP) techniques enable automated extraction and classification of tweets based on their relevance to disasters. Our project, *Disaster Tweet Analyzer*, harnesses these capabilities to analyze tweets, identifying their disaster relevance, sentiment, location, and type. This innovation equips responders, researchers, and stakeholders with actionable insights, enhancing disaster management strategies.

Past Studies

The evolution of disaster tweet analysis is rooted in early attempts to use social media as a disaster response tool. Researchers have developed systems to classify tweets for disaster relevance and categorize them based on the type of event, such as floods or earthquakes. These efforts have demonstrated the potential of NLP techniques to parse large-scale textual data during emergencies [3][4]. However, existing systems often face significant gaps, including incomplete location data, an inability to handle fake or bot-generated tweets, and limited capacity for real-time analysis. Many approaches also struggle with imbalanced datasets, where disaster-relevant tweets are underrepresented, leading to skewed predictions [5].

Our project bridges these gaps by incorporating advanced techniques such as Named Entity Recognition (NER) for location extraction and Synthetic Minority Oversampling (SMOTE) to address class imbalance. Unlike earlier systems, we focused on improving the dataset's reliability by filtering irrelevant and bot-generated tweets. Additionally, while real-time tweet analysis remains a challenge due to limitations in accessing the Twitter API, the project lays the groundwork for future enhancements, including live tweet integration and a Chrome extension for real-time disaster detection [6][7]. These innovations significantly enhance the efficiency and accuracy of disaster tweet analysis, marking a step forward in leveraging social media for disaster management.

DATA & METHODOLOGY

Data Overview and Preprocessing

The dataset utilized in this project is the Kaggle Disaster Tweets dataset, containing 11,370 labeled tweets. Each entry in the dataset includes the text of the tweet, an associated keyword indicative of its content, and location metadata where available. The target column specifies whether the tweet is disaster-related (target = 1) or not (target = 0) [8].

Preprocessing is a crucial step in any machine learning pipeline, particularly when working with unstructured and imbalanced data like tweets. For the Disaster Tweet Analyzer, the preprocessing phase aimed to enhance the quality and usability of the dataset, addressing challenges such as missing data, class imbalance, and irrelevant or synthetic tweets. These steps ensured that the data was not only clean but also representative of the diverse scenarios encountered during disasters. By employing advanced techniques like data augmentation, feature extraction, and sampling strategies, as shown in Fig. 1, the team was able to create a robust foundation for model training and evaluation. The subsequent sections detail the specific problems encountered during preprocessing and the innovative solutions implemented to overcome them.

1. Enhancing the Location Feature

1.1 Data Augmentation and Integration

The incomplete and inconsistent location data required augmentation from external sources like CrisisLex, which added crucial missing entries to the dataset. To better explore disaster

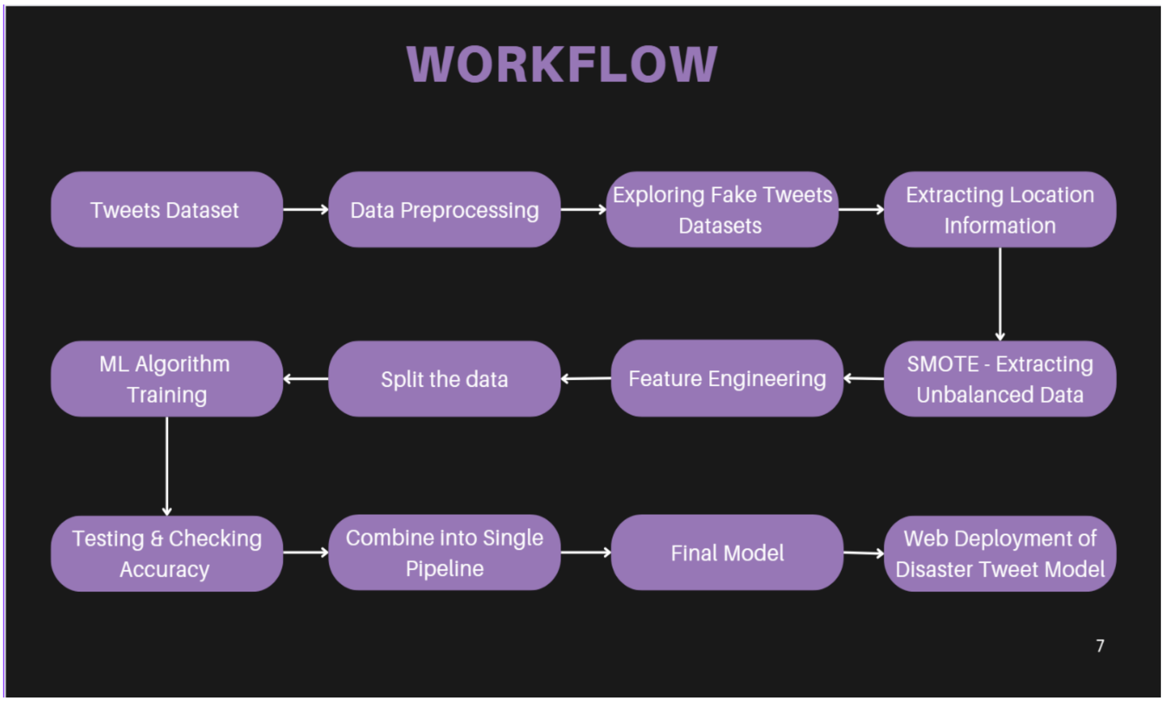

Figure 1: *Workflow*

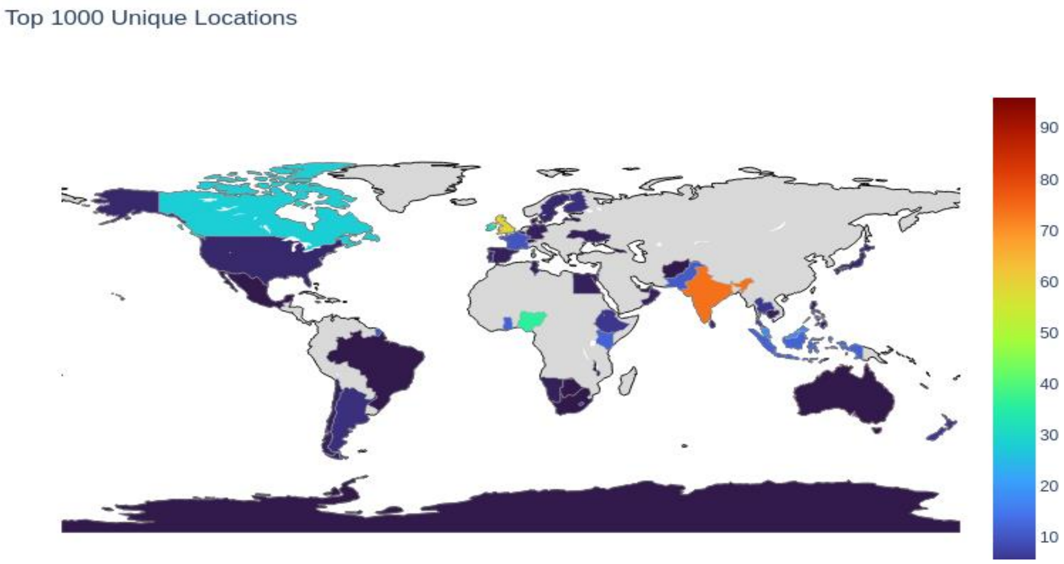

Figure 2: *Top 1000 unique location Extraction around Globe*

relevance tied to location, the team introduced a temporary Target 2 classification, balancing and analyzing data more effectively before reverting to the binary classification. These steps ensured that location data became a more integral part of disaster analysis.

1.2 Location Standardization and Visualization

To make the location feature actionable, advanced techniques like Named Entity Recognition (NER) were used to extract and standardize unstructured text. Visualization tools such as Plotly and Folium were employed to create global location maps as seen in Fig. 2, while shapefiles and Geographic Processing Engines (GPE) allowed for detailed mapping of India-specific locations. These efforts offered new perspectives on location-based insights but also highlighted issues, such as inaccurate geospatial borders in library datasets.

1.3 Model Training and Challenges

The team trained six additional machine learning models, including deep learning algorithms, to assess the impact of improved location data on predictions. These models were tested and integrated into a predictive function that leverages the refined location feature. However, challenges such as data formatting inconsistencies, the complexity of contextualizing over 4,000 unique locations, and the lack of reliable parameters to verify tweet authenticity introduced significant hurdles. Despite these difficulties, the preprocessing efforts vastly improved the dataset's quality, enabling more reliable disaster tweet classification.

2. Integrate Real-Time Tweets

2.1 Efforts to Integrate Real-Time Tweets

One of the project's core aspirations was to incorporate real-time Twitter data to enhance the system's applicability during live disaster scenarios. To achieve this, the team first explored how disaster management teams utilize social media analytics and identified key tools and techniques employed in real-time monitoring. Following this, access to Twitter's API was initiated by creating a developer account, registering an application, and configuring API keys and bearer tokens within the development environment. Using Twitter API v2 endpoints, disaster-related tweets were fetched based on specific keywords and hashtags, laying the groundwork for integrating live data.

Additionally, third-party APIs were explored as alternatives to the Twitter API. These APIs offered basic functionality for retrieving social media data and were tested for their capability to filter disaster-related content. Despite these efforts, real-time data integration remained a challenge due to the limitations posed by access restrictions.

2.2 Challenges and Limitations

The restricted authorization levels of the Twitter API posed a significant hurdle, limiting access to essential features like real-time data scraping. Upgrading to higher access levels required considerable resources, including substantial financial investment and meeting stringent application criteria, which were beyond the scope of the project. Similarly, third-party APIs allowed only limited data retrieval and often returned tweets with insufficient relevance to disaster topics. These constraints ultimately hindered the realization of a fully integrated real-time data solution.

Although real-time tweet integration could not be achieved, the exploratory work laid a solid foundation for future developments. The insights gained from these efforts provide a roadmap for addressing technical and resource-based challenges in subsequent iterations of the project.

3. Integrate Real-Time Tweets

3.1 Efforts in Dataset Creation and Model Training

To improve the model’s ability to identify fake tweets, the team created a new dataset using the **Faker Library**, which generates synthetic tweets. This allowed for the addition of **Target 2** to classify tweets as fake or real, alongside disaster relevance. After preparing the dataset, machine learning models were trained to distinguish between authentic and fake content, and the model's predict function was tested to ensure effective performance in both tasks.

3.2 Challenges and Limitations

One of the main challenges was scaling, as generating large datasets with Faker proved computationally expensive and slow. Additionally, **feature overlap** between the new target and the existing disaster relevance classification reduced the value of **Target 2**. **Labeling errors** during manual annotation also introduced inaccuracies, impacting the model's learning ability.

Despite these challenges, the groundwork for identifying fake tweets has been laid, and future improvements can refine this process with better resources and dataset management.

4. Addressing Dataset Imbalance

4.1 Efforts in Dataset Balancing

During dataset exploration, a significant imbalance was observed between disaster and non-disaster tweets. To address this, the team conducted a literature survey on dataset balancing techniques, understanding the potential drawbacks of both oversampling and under sampling. Oversampling disaster-relevant tweets could compromise the quality, while under sampling would reduce the dataset size, which was already limited to 11,370 tweets.

To mitigate this, various SMOTE (Synthetic Minority Oversampling Technique) techniques, including **SMOTE-ENN**, **SMOTE-NC**, and **Tomek Links**, were explored. These methods aimed to balance the dataset by generating synthetic samples of the minority class without losing valuable information. Each SMOTE variant was applied and tested on multiple machine learning models, including **Logistic Regression, Random Forest, KNN, XGBoost, and Gradient Boosting**.

4.2 Model Evaluation and Challenges

After testing, it was found that **SMOTE-NC** with the **Random Forest** model yielded the best accuracy of 94%. However, this combination also revealed signs of overfitting, where the model performed well on the training data but struggled to generalize on unseen data. To address this, additional steps were taken to reduce overfitting, such as parameter tuning and applying regularization techniques.

While these efforts significantly improved the model's performance, they also highlighted the ongoing challenge of balancing dataset quality with model generalization. Future work can refine these techniques further, ensuring the model remains robust across diverse tweet samples.

Model Evaluation

The Disaster Tweet Analyzer evaluated a range of machine learning models, using accuracy as the primary metric for final selection. To identify the most suitable model for disaster tweet classification, a wide range of machine learning algorithms were tested which are shown in Table 1. Among the models tested were **Logistic Regression**, **Random Forest**, **Linear SVM**, **Gradient Boosting**, **XGBoost**, **KNN**, **Naive Bayes**, **Decision Tree**, **Stochastic Gradient Descent (SGD)**, **CNN**, and **RNN**. After comprehensive evaluation, **Logistic Regression** emerged as the optimal choice, achieving an accuracy of 92% as shown in Fig. 3. Its simplicity, efficiency, and reliable performance made it well-suited for disaster tweet classification, offering a balance of interpretability and robustness for the task.

Table 1: *Comparing Model Accuracy and Precision*

Model Used	**Accuracy**	**Precision**
Linear Regression	**0.91**	**0.87**
Linear SVM	**0.92**	**0.89**
Random Forest	**0.92**	**0.94**
Gradient Boosting	**0.83**	**0.94**
Logistic Regression	**0.92**	**0.89**
XGBoost	**0.85**	**0.94**
KNN	**0.87**	**0.98**
Naive Bayes	**0.90**	**0.88**
CNN	**0.91**	**0.91**
RNN	**0.89**	**0.90**
SGD	**0.91**	**0.89**
Decision Tree	**0.88**	**0.85**

Other models like XGBoost and Decision Trees were also tested for their strengths in handling imbalanced data and non-linear relationships. Ultimately, Logistic Regression emerged as the

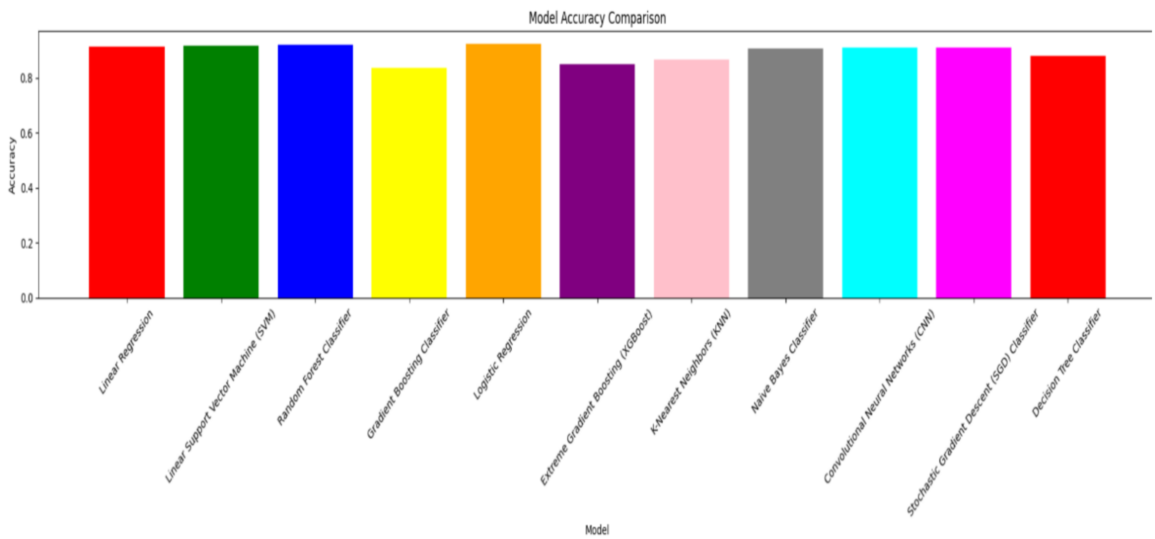

Figure 3: *Model Accuracy Comparison Chart*

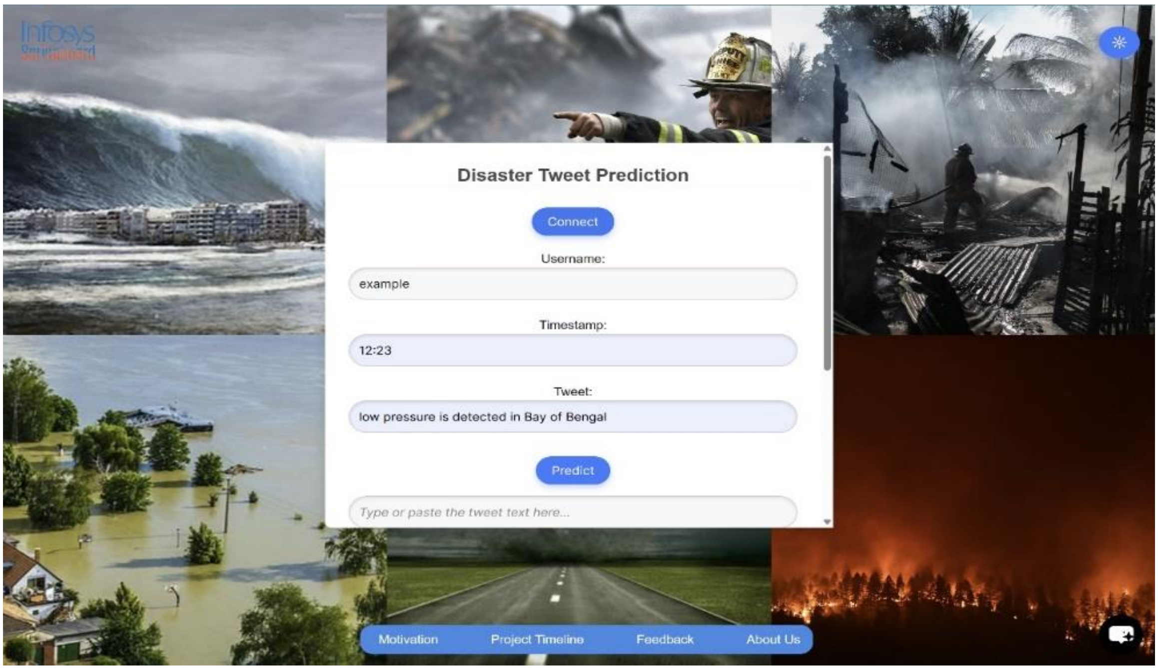

Figure 4: *Real-time information gathering*

preferred model, striking a balance between simplicity, interpretability, and predictive power.

Model Integration and Web Interface

The Disaster Tweet Analyser was designed to provide a user-friendly interface accessible through a dedicated website, combining the power of machine learning with seamless user interaction which can be seen in the Fig. 4 & Fig. 5. The website was developed to allow users to input a tweet and obtain a comprehensive analysis, including disaster relevance, the tweet's location, disaster category, and sentiment. These insights are generated through the backend machine learning model integrated with the platform.

To enhance functionality, a chatbot, **Tarini**, was incorporated into the website. Powered by ChatGPT, this chatbot acts as an intelligent assistant, allowing users to ask questions, seek additional disaster-related information, and receive contextual guidance. Tarini bridges the gap between static model predictions and dynamic user queries, making the platform more interactive and informative.

Another key feature is a dedicated tab providing insights into the project's **motivation and workflow timeline**, offering users a transparent view of the journey behind the Disaster Tweet Analyser. This tab highlights the importance of real-time disaster information, the challenges encountered during development, and the step-by-step methodology implemented to bring the project to life.

An experimental feature for reporting Twitter tweets was conceptualized, enabling users to flag tweets relevant to disaster response and provide supplementary details for authorities or analysts. Additionally, a **Connect** button was integrated, allowing users to directly access the

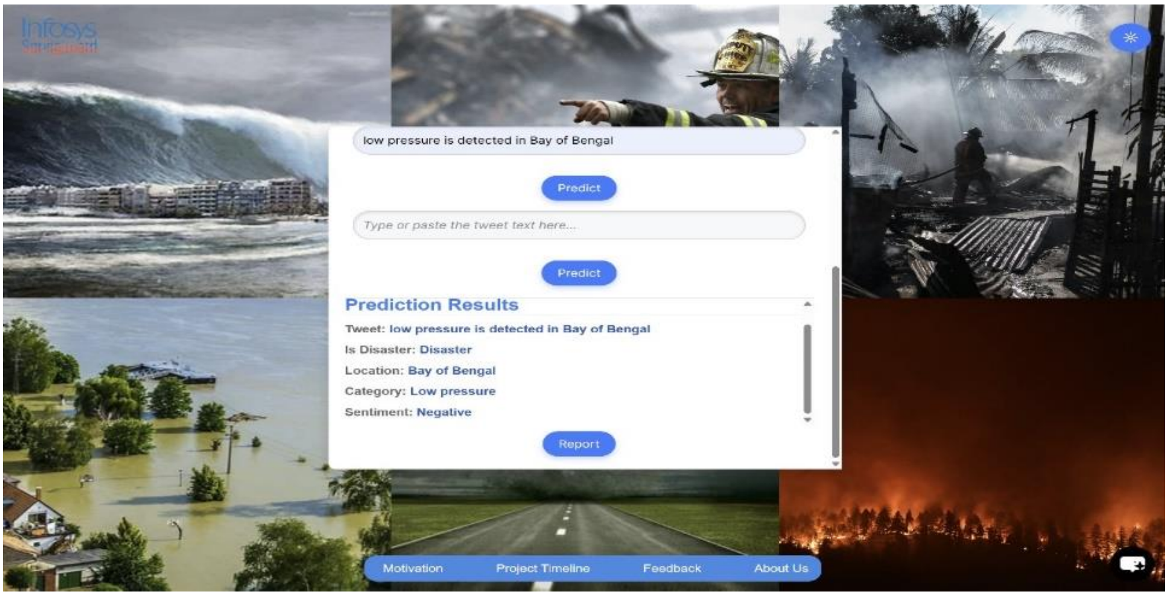

Figure 5: *Relevant Disaster tweet Prediction*

Twitter login page for seamless interaction. Input boxes for entering the username and timestamp of the tweet were also added, enabling users to provide real-time and more relevant information. While this milestone was not fully implemented due to time constraints, these features lay a strong foundation for future enhancements, aiming to improve disaster response collaboration and accuracy.

The website's technical implementation employed frameworks like **Flask** for rapid prototyping and interactive widgets, enabling smooth user input and output visualization. The interface integrates an input box where users can paste tweets and instantly view results by clicking on "Predict." The chatbot, motivation tab, and conceptual reporting feature make the website not just a tool for prediction but also a hub for disaster-related exploration and interaction.

CONCLUSIONS AND FUTURE DIRECTIONS

The Disaster Tweet Analyzer project successfully demonstrates the potential of machine learning and natural language processing in identifying and analyzing disaster-related tweets. By leveraging the Kaggle Disaster Tweets dataset, the system accurately classifies tweets as disaster-related or not while providing auxiliary insights such as the disaster's location, type, and sentiment. This information is invaluable for emergency responders, policymakers, and analysts to understand real-time disaster scenarios and deploy resources efficiently. Key achievements include building an accurate model using techniques such as SMOTE for handling class imbalance and integrating the system into a user-friendly web interface. The addition of a chatbot, Tarini, further enhances user engagement by providing detailed, AI-driven information about disasters. These accomplishments underscore the utility and relevance of this project in addressing real-world challenges during disaster situations.

However, certain challenges and limitations highlight the scope for future work. The inability to fully utilize Twitter's API due to access restrictions limited the system's ability to perform real-time tweet analysis. Addressing this constraint in the future could enable the seamless integration of live disaster data. Additionally, while the concept of flagging tweets for disaster reporting was explored, time constraints prevented its implementation. This feature, combined with user-submitted information, could significantly augment the system's impact by fostering collaboration between the public and emergency services.

Future directions also include improving disaster tweet authenticity checks to filter out false or misleading information and enhancing the system's capability to extract and verify granular location details. Expanding the model to classify multilingual tweets would increase its applicability in diverse geographical regions. Furthermore, transitioning the platform into a Chrome extension could facilitate real-time tweet analysis directly on social media platforms, delivering instant results on disaster relevance and sentiment.

In conclusion, this project lays a strong foundation for harnessing social media data during disasters, with significant achievements and promising avenues for future development. By addressing existing limitations and embracing new technologies, the Disaster Tweet Analyzer has the potential to evolve into a comprehensive tool for disaster response and management.

ACKNOWLEDGEMENTS

We express our sincere gratitude to our mentor, Mr. Nitig Singh from Infosys Springboard, for his invaluable guidance throughout this project on disaster tweet analysis. We are also thankful to Infosys and the Infosys Springboard Committee for the opportunity to work on a project that blends learning with practical application. Special thanks to our team leads and co-leads for their dedicated efforts and leadership, as well as to every team member whose diverse skills contributed to our success. The Kaggle Disaster Tweets dataset was instrumental in this project, which has been a transformative learning experience for all involved.

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