

Intelligent Tweet Analyzer for Disaster Management

Submitted in partial fulfillment of the requirements of the degree of

BACHELOR OF ENGINEERING

by

Hetal Mahajan : 21106014

Christina D'Cruz : 22106024

Prabudh Gaikwad : 21106038

Guide:

Dr. Rahul K Ambekar



Department of Computer Science & Engineering

(Artificial Intelligence & Machine Learning)

A. P. SHAH INSTITUTE OF TECHNOLOGY, THANE

(2025-2026)



A. P. SHAH INSTITUTE OF TECHNOLOGY, THANE

CERTIFICATE

This is to certify that the project entitled "**Intelligent Tweet analyzer for Disaster Management**" is a bonafide work of **Hetal Mahajan (21106014)**, **Christina D'Cruz (22106024)**, **Prabudh Gaikwad (21106038)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **Bachelor of Engineering in Computer Science & Engineering (Artificial Intelligence & Machine Learning)**.

Dr. Rahul K Ambekar
Guide

Prof. Sayali P. Badhan
Project Coordinator

Dr. Jaya Gupta
Head of Department

Dr. Uttam D. Kolekar
Principal



A.P. SHAH INSTITUTE OF TECHNOLOGY, THANE

Project Report Approval for B.E.

This project report entitled "*Intelligent Tweet Analyzer for Disaster Management*" by "*Hetal Mahajan, Christina D'Cruz and Prabudh Gaikwad*" is approved for the degree of **Bachelor of Engineering in Computer Science & Engineering (Artificial Intelligence & Machine Learning), 2025-26.**

Examiner Name

1. _____
2. _____

Signature

Date:

Place:

Declaration

We declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

(Hetal Mahajan - 21106014)

(Christina D'Cruz - 22106024)

(Prabudh Gaikwad - 21106038)

Date:

Abstract

In recent years, social media platforms such as Twitter (now X) have emerged as critical tools for real-time information exchange during disaster situations. This project, *Tweet Analysis for Disaster Management*, aims to harness the potential of Twitter data to support faster, data-driven decision-making during crises like floods, earthquakes, and pandemics. The system utilizes Natural Language Processing (NLP) and Machine Learning (ML) techniques to automatically analyze tweets, extract relevant information, and categorize them into actionable types such as Help Requests, Rescue Updates, Blood Donations, and General Information. By integrating geolocation tagging, sentiment analysis, and urgency scoring, the proposed framework enhances situational awareness and enables disaster response teams to prioritize resources effectively. The architecture combines real-time data collection, AI-powered tweet classification, and visualization modules to support timely and targeted interventions. The system addresses challenges such as noisy and multilingual tweet data, ensuring scalability and adaptability across diverse disaster scenarios. Overall, this approach bridges the gap between social media intelligence and operational disaster management, improving response efficiency, coordination, and life-saving outcomes.

Keywords: Disaster Management, Twitter Analysis, NLP, Machine Learning, Sentiment Analysis, Real-Time Response, Geolocation, Emergency Classification

CONTENTS

1. Introduction.....	1
2. Literature Survey.....	3
3. Limitation of Existing System.....	5
4. Problem Statement, Objectives and Scope.....	9
5. Proposed System.....	10
6. Experimental Setup.....	18
7. Project Plan.....	0
8. Expected Outcome.....	0
References.....	0

LIST OF FIGURES

5.1 Proposed System.....	9
7.1 Gantt Chart.....	18
8.1 Expected Outcome.....	19-20

LIST OF TABLES

2.1 Literature Survey.....	4- 5
----------------------------	------

ABBREVIATION

CN	<i>Computer Network</i>
ABE	<i>Attribute Based Encryption</i>

Chapter 1

Introduction

Social media platforms, particularly Twitter (now X), have become vital real-time information channels during disaster situations, offering a dynamic and immediate source of data that traditional methods, such as news reports or official emergency channels, often cannot match in speed or granularity. In crises like hurricanes, earthquakes, floods, or pandemics, individuals use Twitter to share critical updates, report on-the-ground conditions, request urgent assistance (e.g., medical aid, food, or shelter), offer support (e.g., donations or volunteer services), and disseminate situational awareness (e.g., road closures or safe zones). This user-generated content provides a wealth of real-time, geospatially relevant information that can significantly enhance disaster management efforts, enabling faster decision-making and resource allocation to save lives and mitigate impacts.

However, the sheer volume, velocity, and variety of tweets during disasters present significant challenges. Millions of tweets may be posted within hours, as seen during Hurricane Ian (2023), where over 20 million tweets were analyzed to understand public responses. These tweets are often noisy, containing informal language, slang, emojis, or irrelevant content, which complicates the identification of urgent needs. For instance, distinguishing a genuine help request from a sarcastic comment or a general expression of concern requires sophisticated processing, as noted by Arvandi et al. (2024). Manual analysis of such data is infeasible due to the scale and time sensitivity, leading to delays in recognizing critical information, such as requests for rescue or medical supplies. Additionally, the diversity of tweet content—ranging from emotional outbursts to actionable updates—further hinders the ability of first responders and non-governmental organizations (NGOs) to prioritize and act on the most pressing needs.

To address these challenges, the proposed solution is to develop an automated system that leverages advanced natural language processing (NLP) and machine learning techniques to classify tweets into actionable categories, such as Help Request, Blood Donation, Rescue Update, Resource Availability, and General Information. This system would employ algorithms like sentiment analysis, topic modeling, and deep learning models (e.g., BiLSTM-CNN, as used in the 2019 study on Hurricanes Harvey and Irma) to filter and categorize tweets with high accuracy. For example, a tweet stating,

“Urgent: Need blood type O+ in Chennai hospital” could be classified as a Blood Donation request, while “Rescue team reached Main Street” could be tagged as a Rescue Update. By incorporating geolocation data and sentiment analysis, as demonstrated in the Chennai flood study (2017), the system can prioritize tweets based on urgency and location, enabling targeted responses.

The impact of such a system is profound for disaster management. By automating the classification of tweets, it enables first responders, NGOs, and government agencies to quickly identify and prioritize urgent needs, such as dispatching rescue teams to stranded individuals or directing medical supplies to areas with critical shortages. This enhances coordination, reduces response times, and optimizes resource allocation, ultimately saving lives and improving efficiency. For instance, Shekhar and Setty (2015) showed how sentiment-based visualization of tweets can map distress levels, aiding responders in focusing on high-priority areas. Furthermore, by integrating with existing disaster management frameworks, the system can bridge the gap between social media insights and operational workflows, addressing a key limitation noted by Arvandi et al. (2024). Despite challenges like noisy data, multilingual content, and computational demands, as highlighted in the literature, this solution offers a scalable, real-time approach to harness Twitter’s potential, making it a game-changer for effective disaster response.

Real-Time Information Hub: Social media platforms, particularly Twitter (now X), serve as critical channels during disasters like hurricanes, earthquakes, floods, or pandemics, providing immediate, user-generated updates that outpace traditional sources like news or official reports.

User Contributions: Individuals post about emergencies (e.g., stranded locations), request help (e.g., medical aid, food), offer support (e.g., donations, volunteering), and share updates (e.g., road closures, safe zones), offering valuable on-the-ground insights.

Sustainability Development Goal Alignment

- **SDG 11: Sustainable Cities and Communities**

The system enhances the ability of cities and communities to prepare for, respond to, and recover from disasters.

By analyzing tweets for real-time information on emergencies, it helps authorities coordinate rescue operations and resource allocation efficiently, contributing to disaster-resilient infrastructure and sustainable urban management.

- **SDG 9: Industry, Innovation, and Infrastructure**

The system demonstrates innovative use of emerging technologies like Natural Language Processing (NLP), Machine Learning (ML), and Large Language Models (LLMs) for societal benefit.

It promotes the integration of digital infrastructure in emergency management systems.

Chapter 2

Literature Survey

Year	Title	Domain	Algorithm	Dataset	Gap
2024	Twitter Analysis in Emergency Management: Recent Research and Trends	Disaster Management, Social Media Analysis	Sentiment Analysis, Topic Modeling, Geolocation-based Analysis	Various disaster-related tweet datasets (e.g., hurricanes, earthquakes) from the past five years	Limited discussion on multilingual tweet analysis and integration with traditional disaster management systems, which restricts applicability in diverse regions and operational settings.
2023	Social Response and Disaster Management: Insights from Twitter Data Assimilation on Hurricane Ian	Disaster Management, NLP, Spatiotemporal Analysis	Sentiment Analysis, Topic Modeling	Over 20 million tweets from Hurricane Ian (2022)	Limited handling of noisy or irrelevant tweets, which reduces the accuracy of spatiotemporal insights, and no mention of multimodal

					(e.g., image) analysis.
2019	A Deep Learning Approach for Tweet Classification and Rescue Scheduling for Effective Disaster Management	Disaster Management , Deep Learning	Attention-based BiLSTM, CNN, Feature Engineering	Tweets from Hurricane s Harvey and Irma	Dependence on labeled datasets and high computational requirements, limiting scalability for real-time use in resource-constrained environments.
2017	Usage and Analysis of Twitter During 2015 Chennai Flood Towards Disaster Management	Disaster Management , Information Propagation	Random Forests, Other Machine Learning Algorithms	Tweets from the 2015 Chennai Flood	Limited focus on non-English (e.g., Tamil) tweets and lack of integration with real-world disaster response systems, reducing practical utility.
2015	Disaster Analysis Through Tweets	Disaster Management , Sentiment Analysis	Sentiment Classification, Visualization Techniques	Tweet datasets from natural disasters (specific disasters not detailed in the abstract)	Lack of focus on non-English tweets and limited generalizability to different disaster types, potentially missing critical insights from diverse populations.

- [1] In 2024, the paper “*Twitter Analysis in Emergency Management: Recent Research and Trends*” examined various methods for analyzing social media data during disasters. This study focused on domains such as disaster management and social media analysis, employing techniques like sentiment analysis, topic modeling, and geolocation-based analysis. The research utilized diverse tweet datasets related to hurricanes and earthquakes collected over the past five years. However, it highlighted a significant gap—the limited discussion of multilingual tweet analysis and integration with traditional disaster management systems, which restricts its applicability across diverse regions and operational contexts.
- [2] In 2023, the study “*Social Response and Disaster Management: Insights from Twitter Data Assimilation on Hurricane Ian*” focused on natural language processing (NLP) and spatiotemporal analysis to assess public sentiment and response during Hurricane Ian (2022). Using a dataset of over 20 million tweets, the researchers applied sentiment analysis and topic modeling to derive insights. Despite its robust scale, the study struggled with noisy or irrelevant tweets, which impacted the precision of spatiotemporal insights, and it did not include multimodal data such as images, limiting the richness of disaster analysis.
- [3] A 2019 study titled “*A Deep Learning Approach for Tweet Classification and Rescue Scheduling for Effective Disaster Management*” introduced deep learning methods like Attention-based BiLSTM, CNN, and advanced feature engineering for tweet classification and rescue coordination. Using tweets from Hurricanes Harvey and Irma, this work improved tweet classification accuracy. However, it relied heavily on labeled datasets and required high computational resources, posing challenges for real-time use in resource-constrained environments.

[4] In 2017, the paper “*Usage and Analysis of Twitter During 2015 Chennai Flood Towards Disaster Management*” applied Random Forests and other machine learning algorithms to study information propagation on social media during the 2015 Chennai floods. Although it provided useful insights into how Twitter facilitates real-time communication during crises, the research had limited focus on non-English (particularly Tamil) tweets and lacked integration with operational disaster response systems, reducing its real-world utility.

[5] In 2015, the study “*Disaster Analysis Through Tweets*” explored sentiment classification and visualization techniques to interpret social media data during natural disasters. The study utilized tweet datasets from various disasters, although it did not specify which events. While it presented foundational ideas in disaster sentiment analysis, it had key limitations such as ignoring non-English tweets and offering limited generalizability across disaster types, potentially missing valuable insights from diverse populations.

Chapter 3

Limitations of Existing Systems

The use of Twitter (now X) for disaster management has shown great potential, but existing systems face several limitations that hinder their effectiveness. Below is a concise overview of the key limitations, tailored for your project report, based on the reviewed literature and general challenges in the field.

1. **Noisy and Unstructured Data:** Tweets often include slang, emojis, misspellings, or irrelevant content, complicating accurate information extraction. This noise can lead to misclassification of urgent needs, such as mistaking sarcastic posts for genuine distress calls.
2. **Limited Generalizability:** Systems trained on specific disasters (e.g., hurricanes) often perform poorly on others (e.g., pandemics), requiring retraining and limiting their scalability across diverse crisis scenarios.
3. **Language and Data Bias:** Most systems focus on English tweets, excluding non-English-speaking communities, and urban user dominance skews insights, potentially overlooking rural or underrepresented groups.
4. **Real-Time Processing Challenges:** Analyzing millions of tweets in real time demands high computational resources, causing delays that can impede timely disaster response.
5. **Lack of Actionability:** Distinguishing actionable tweets (e.g., help requests) from general commentary is difficult, reducing the ability to prioritize critical needs effectively.

Twitter's potential in disaster management is significant, but current systems face limitations. The noisy and unstructured nature of tweet data, including informal language, complicates natural language processing, leading to misclassification of critical information. Limited generalizability across different disaster types and language biases also hinder their utility. Real-time processing constraints and lack of actionability in tweet classification further hinder performance. To improve tweet analysis systems, advancements in noise reduction, multilingual and multimodal analysis, scalable processing, and integration with operational disaster management frameworks are needed.

Chapter 4

Problem Statement, Objectives and Scope

Problem Statement

During disaster situations, Twitter (now X) serves as a critical real-time information channel, with users posting updates, help requests, and support offers. However, the high volume, noise, and unstructured nature of tweets make it challenging to quickly identify and prioritize actionable information, such as urgent needs or critical updates, hindering effective disaster response. Existing systems struggle with noisy data, limited generalizability across disaster types, and language biases, often failing to extract precise location data or assess the urgency of tweets accurately. The proposed solution aims to develop an automated system that addresses these challenges by: extracting and tagging locations for affected areas to enable geospatial prioritization; scoring urgency and performing sentiment analysis for distress detection to identify critical needs; and categorizing tweets into actionable emergencies (e.g., Help Request, Blood Donation, Rescue Update) to facilitate rapid and targeted responses by first responders and NGOs. This system seeks to enhance disaster management efficiency, reduce response times, and improve resource allocation to save lives and mitigate impacts.

Objectives

The primary objective of this project is to develop an automated system for analyzing Twitter (now X) data to enhance disaster management by enabling rapid and effective response coordination. Specifically, the system aims to: extract and tag locations for affected areas to facilitate geospatial prioritization of rescue and relief efforts; score urgency and perform sentiment analysis for distress detection to identify critical needs and prioritize high-priority cases; and categorize tweets into actionable emergencies (e.g., Help Request, Blood Donation, Rescue Update) to streamline decision-making for first responders and NGOs. By addressing challenges like data noise and limited generalizability, the system seeks to improve response times, optimize resource allocation, and ultimately save lives during disasters.

Scope

The scope of this project involves developing an automated system to analyze Twitter (now X) data for enhancing disaster management during crises such as hurricanes, floods, earthquakes, and pandemics. The system will focus on: extracting and tagging locations from tweets to map affected areas for targeted response; scoring urgency and conducting sentiment analysis to detect distress and prioritize critical needs; and categorizing tweets into actionable emergencies (e.g., Help Request, Blood Donation, Rescue Update) to facilitate rapid decision-making by first responders and NGOs. The project will leverage natural language processing (NLP) and machine learning techniques, such as BiLSTM-CNN and Random Forests, to process large-scale, real-time tweet data while addressing challenges like noise, multilingual content, and computational demands. The system aims to integrate with existing disaster management frameworks to improve response efficiency, resource allocation, and situational awareness, with potential applications in real-time monitoring, rescue prioritization, and public sentiment tracking across diverse disaster scenarios.

- **Location Extraction and Tagging:** Map affected areas from tweets for targeted rescue and relief efforts.
- **Urgency Scoring and Sentiment Analysis:** Detect distress and prioritize critical needs using real-time analysis.
- **Actionable Tweet Categorization:** Classify tweets into categories like Help Request, Blood Donation, and Rescue Update for rapid response coordination.

Chapter 5

Proposed System

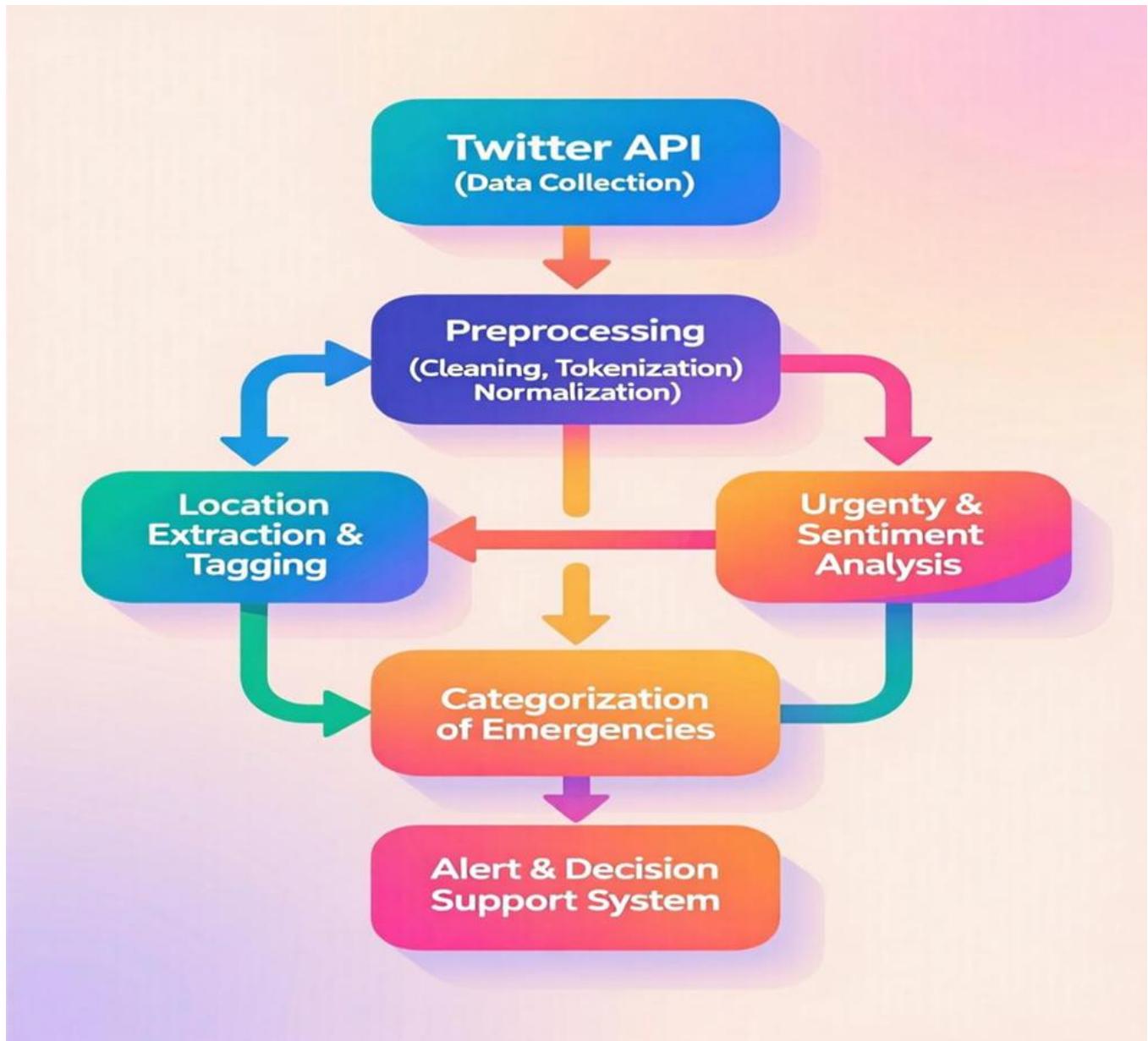


Figure 5.1 Architecture Diagram for MedIntel

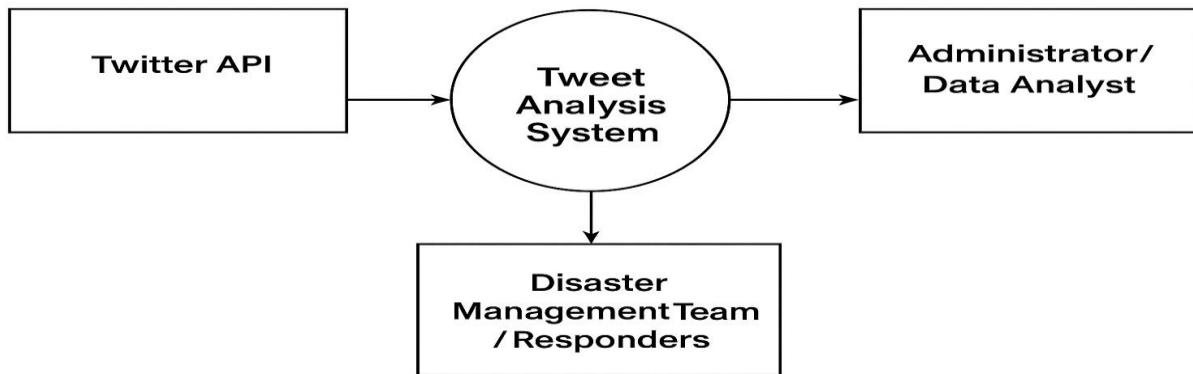
This diagram illustrates the workflow of a Name of The System and Explanation of the diagram

Data Flow Diagrams:

The Data Flow represents the logical flow of information within the Tweet Analysis for Disaster Management System. It illustrates how raw tweet data moves through various processes — from collection to analysis and finally visualization — to support timely disaster response and decision-making.

Context Level DFD (Level 0)

Context Level DFD (Level 0)



At the highest level, the system interacts with three primary external entities:

- Twitter API: Provides real-time disaster-related tweets that serve as the raw data input for the system.
- Administrator / Data Analyst: Manages system configuration, monitors analytics, and validates outputs.
- Disaster Management Team / Responders: Utilize the processed results, such as alerts and situational insights, to coordinate rescue and relief efforts.

The Tweet Analysis System acts as a central processor that:

1. Fetches tweets from the Twitter API based on disaster-related keywords and geolocation filters.
2. Processes and classifies tweets into predefined categories such as *Help Request*, *Rescue Update*, *Blood Donation*, or *General Information*.

- Generates visual dashboards and alerts for use by analysts and responders.

Level 1 DFD

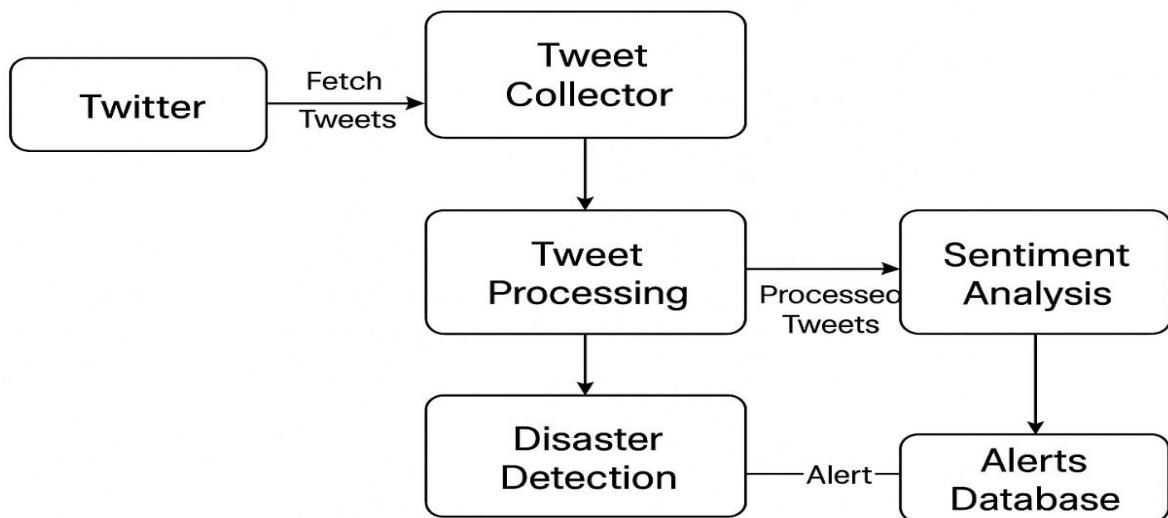


Figure 1: Level 1 diagram for Intelligent Tweet Analyzer

The Level 1 DFD breaks down the internal functions of the system into detailed modules:

1. Process 1.0 – Data Collection Module

- Input: Tweets from Twitter API.
- Function: Continuously collects tweets related to disasters using keyword and location-based filters.
- Output: Raw tweets stored in the Tweet Database.

2. Process 2.0 – Data Preprocessing Module

- Input: Raw tweet data.
- Function: Cleans and normalizes tweets by removing stop words, URLs, special characters, and emojis.
- Output: Cleaned tweets ready for feature extraction.

3. Process 3.0 – Feature Extraction & Classification Module

- Input: Cleaned tweets.

- Function: Converts text into numerical embeddings (TF-IDF or word vectors) and uses NLP models (such as Google Gemini LLM or BiLSTM-CNN) to classify tweets into actionable categories based on urgency or content type.

- Output: Classified tweets stored in the Processed Data Repository.

4. Process 4.0 – Analytics & Visualization Module

- Input: Classified tweet data.

- Function: Aggregates and analyzes results to generate insights such as *tweet density per region, resource demand hotspots, and sentiment patterns*.

- Output: Interactive dashboards, heatmaps, and analytical reports displayed to the disaster management team.

5. Process 5.0 – Alert Generation Module

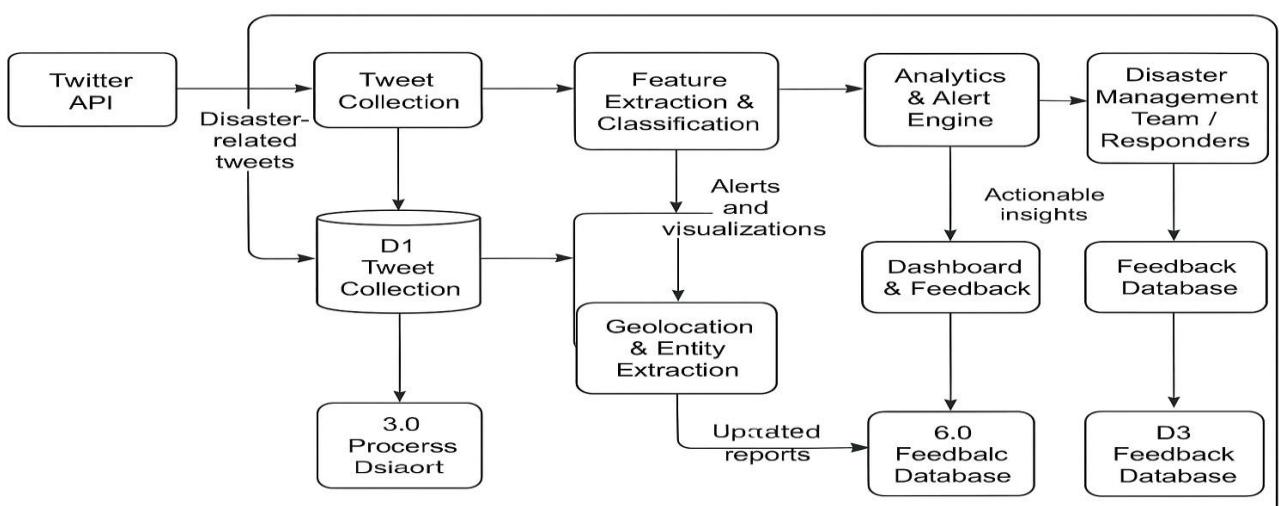
- Input: High-urgency tweets and classification results.

- Function: Automatically generates alerts for first responders and NGOs.

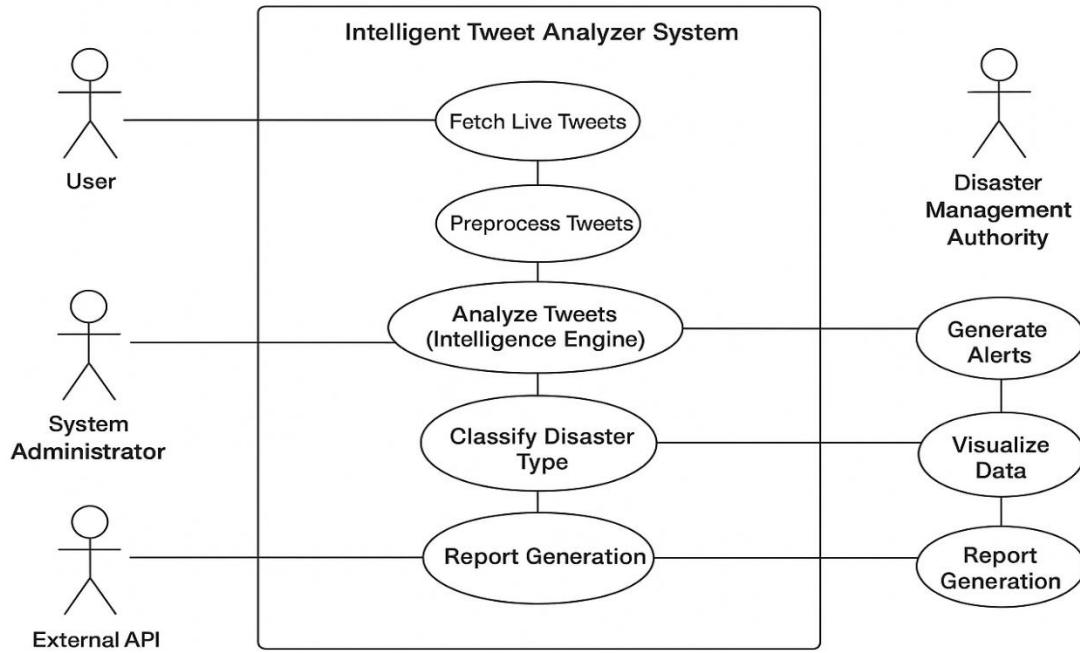
- Output: Notifications and alerts sent to the disaster management dashboard or mobile devices

Level 2 DFD

Level 2 DFD



Use Case Diagram:



Actors:

- System Administrator / Data Engineer
- Disaster Response Personnel / Analyst / User
- External Data Source (Twitter / Social API)

Use Cases:

- Collect Tweets
- Clean / Filter Tweets
- Train Classification Model
- Classify Tweets
- Extract Location
- Generate Alert
- View Dashboard / Map
- Provide Feedback (label correction)
- Retrain Model

Sequence Diagram:

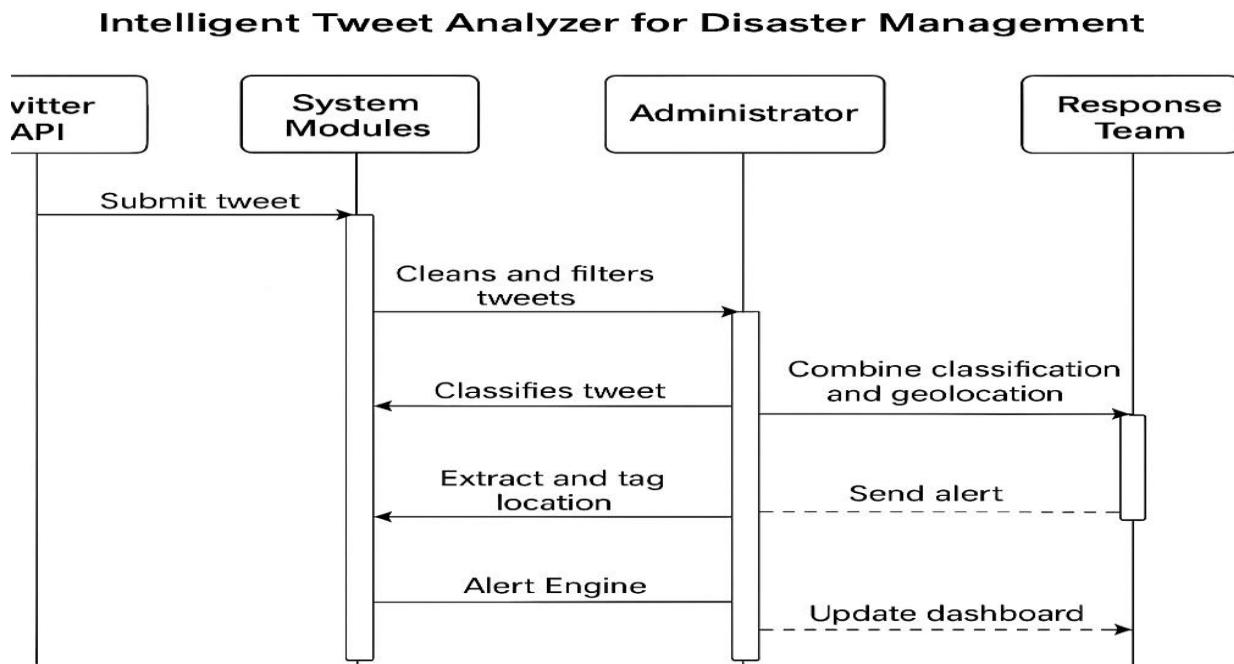
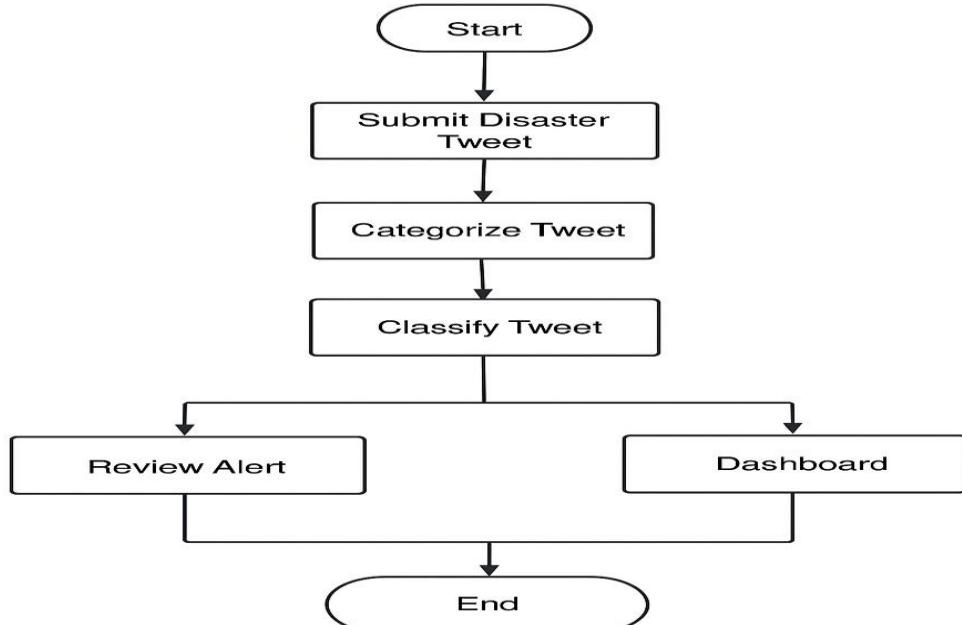


Figure 5.6: Sequence Diagram for Intelligent Tweet Analyzer for Disaster Management

Sequence:

- Twitter API → sends tweet to Tweet Collector
- Tweet Collector → sends the tweet to Preprocessor
- Preprocessor → returns cleaned/filtered tweet to Classifier
- Classifier → returns classification (e.g. “flood, high severity”)
- Classifier → sends to Geolocation Module (maybe concurrently)
- Geolocation Module → returns location coordinates
- Classifier + Location → sent to Alert Engine
- Alert Engine → decides whether to trigger alert
- If yes, Alert Engine → sends alert info to Dashboard / UI
- Dashboard updates the map, shows alert to user

Activity Diagram:



Activity Diagram for Intelligent Tweet Analyzer for Disasters

The **Activity Diagram** represents the dynamic workflow of the Tweet Analysis for Disaster Management System, showing the sequence of operations performed from data collection to disaster response decision-making. It highlights how raw tweet data moves through the system, the processing stages involved, and the actions taken by users and the system at each step.

Step-by-Step Workflow Description

- **Start** – The process begins when the system is activated to monitor disaster-related tweets in real time.
- **Tweet Collection** –
The system connects to the **Twitter API** and fetches tweets using predefined disaster-related keywords (e.g., flood, earthquake, rescue) and location filters.

- **DataStorage**—The collected tweets are temporarily stored in the **Raw Tweet Database** for preprocessing and further analysis.

- **Data Preprocessing** –

The system performs text cleaning and normalization, including removal of URLs, stopwords, hashtags, emojis, and special characters.

- **Decision Node:** If the tweet is invalid or empty after cleaning → it is discarded.
- Otherwise → it proceeds to the next step.

1. **Feature Extraction** –

The cleaned tweets are tokenized and converted into numerical vectors using techniques like **TF-IDF** or **word embeddings** for machine learning analysis.

2. **Tweet Classification (Core Analysis)** –

The preprocessed data is passed to the **Google Gemini LLM** or an ML model (BiLSTM-CNN or Random Forest) to classify each tweet into one of the following categories:

- Help Request
- Rescue Update
- Blood Donation
- Resource Availability
- General Information

3. **Entity Extraction (NER)** –

The model identifies **key entities** (locations, victim counts, resources like “food” or “ambulance”) to add context to each tweet.

4. **Store Classified Data** –

The results are stored in the **Classified Data Repository**, tagged with labels and urgency scores.

5. **Analytics and Visualization** –

The **Analytics Engine** aggregates data to generate insights such as sentiment trends, disaster hotspots, and resource requirements.

These insights are displayed on an interactive **Dashboard** featuring maps, charts, and real-time analytics.

6. Alert Generation –

If a tweet is classified as urgent (e.g., life-threatening situations), the system automatically generates **alerts** for first responders or NGOs.

7. Response Action –

The **Disaster Management Team** or **Rescue Workers** receive the alert and take appropriate action (dispatching rescue teams, allocating resources, etc.).

8. End –

The activity concludes once data is stored, visualized, and necessary actions have been initiated.

Key Components of the Proposed Framework:

- Frontend (React): User interface, data visualization, map, analytics, alert display.
- Backend (FastAPI): REST API, incident processing, analytics, alert generation, CORS, RSS monitoring.
- Database (MongoDB): Stores incidents, alerts, analytics summaries.
- Gemini Agent: AI-powered content analysis for incident relevance, severity, and alert generation.
- RSS Monitor: Periodically fetches and processes disaster-related RSS feeds.
- Models (Pydantic): Data validation and serialization for API responses.

Analysis:

Strengths:

- Modular architecture (clear separation of frontend, backend, AI, and data).
- Real-time disaster monitoring via RSS and AI analysis.
- Scalable REST API with modern Python stack.
- Extensible for new data sources or analytics.

Weaknesses:

- Reliance on external RSS feeds (may be blocked or rate-limited).
- AI analysis latency (Gemini API response time).
- CORS/configuration issues may affect frontend-backend integration.

Opportunities:

- Add more data sources (social media, sensors).
- Enhance analytics (trend prediction, geospatial clustering).
- Improve alerting (push notifications, SMS integration).

Threats:

- API changes or deprecation (Gemini, RSS).
- Data privacy and security concerns.
- Scalability under high load.

Chapter 6

Experimental Setup

Software Requirements:

- Operating System: Windows 10/11, Linux (Ubuntu 22.04 LTS recommended)
- Programming Languages: Python 3.10+, JavaScript (for front-end)
- Web Frameworks: FastAPI (backend API), React.js (frontend)
- Database: MongoDB (for raw and processed tweet data)
- Visualization Tools: Plotly, Matplotlib, Seaborn (for charts and heatmaps)
- APIs: Twitter API (data collection), Google Gemini API (AI/NLP processing), Google Maps API (geolocation)
- Development Tools: Visual Studio Code, GitHub Codespaces, Jupyter Notebook
- Version Control: Git & GitHub for collaborative development and version tracking

Hardware Requirements

- Minimum Configuration:

Processor: Dual-Core CPU (2.0 GHz or above)

RAM: 8 GB

Storage: 10 GB free space

- Recommended Configuration:

Processor: Quad-Core CPU (Intel i5/i7 or AMD equivalent)

RAM: 16 GB or higher

Storage: 100 GB SSD

Internet: Stable broadband connection for real-time tweet streaming and API calls

- Devices Used: Laptop, Desktop, and Smartphone (for dashboard monitoring and mobile alerts)

Development Environment

- Platform: GitHub Codespaces (hosted on Microsoft Azure Virtual Machine)
- Environment Details: Linux OS with 4-core CPU, 16 GB RAM, pre-configured Python and Node.js
- Containerization: Docker used for environment consistency across development and testing stages
- Agents & AI Assistants: GitHub Copilot and Emergent AI for assisted coding, debugging, and documentation
- Versioning: Each system module (frontend, backend, ML model) maintained in independent Git branches for modular deployment
- CI/CD Pipeline: GitHub Actions for automated testing, integration, and deployment to staging environment

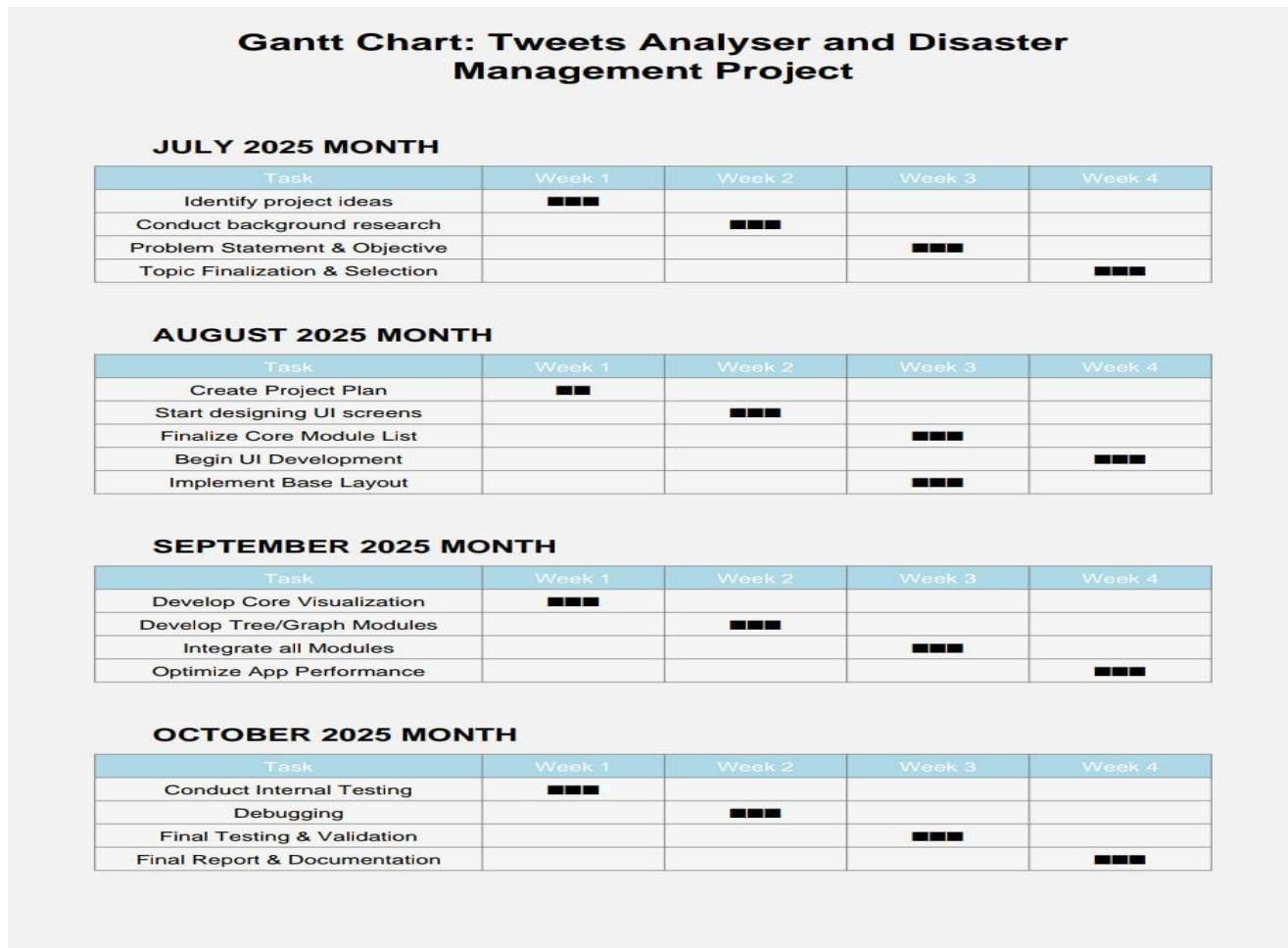
ML/NLP Libraries and Frameworks

- Google Gemini LLM: Core NLP model for text classification, sentiment analysis, and named entity recognition (NER)
- Google Generative AI: Used for text summarization and semantic understanding
- Scikit-learn: Classical machine learning algorithms (Random Forest, SVM, Logistic Regression)
- TensorFlow / PyTorch: For deep learning-based classification and fine-tuning
- Hugging Face Transformers: For tokenization, embedding generation, and pre-trained NLP models
- NLTK / SpaCy: For text cleaning, lemmatization, and stopword removal
- Pandas / NumPy: For structured data manipulation and analysis
- Matplotlib / Seaborn: For generating performance visualizations and analytics dashboards

Chapter 7

Project Planning

Gantt Chart:



Chapter 8

EXPECTED OUTCOME

DisasterWatch

Dashboard Map View Analytics Alerts Search incidents... ☰

Emergency Response Dashboard

Real-time monitoring of emergency incidents and disaster management

Active Alerts: 9 (▲ +12%)

Critical Incidents: 8 (▲ +3)

Total Incidents: 34 (🕒 Live) (▲ +23%)

Avg Urgency: 6 (🕒 Live) (▲ +18%)

Live Incident Feed

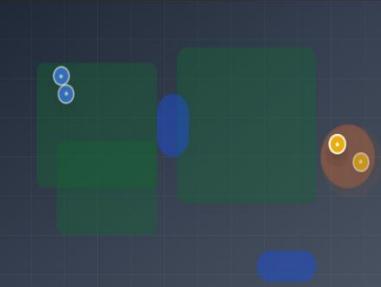
USGS Earthquake Alerts 5 hours ago • Coso Junction, CA (low)

M 2.8 - 15 km E of Coso Junction, CA. [Did You Feel It?](https://earthquake.usgs.gov/earthquakes/eventpage/g41106015#dyfi) maximum reported intensity (1 reports) DYFI? - IV </p> <dl> <dt>Time</dt> <dd>2025-10-10 04:39:09 UTC</dd> <dd>2025-10-10 04:39:09 UTC at epicenter</dd> <dt>Location</dt> <dd>36.035°N 117.780°W</dd> <dt>Depth</dt> <dd>2.69 km (1.67 mi)</dd> </dl>



Live Incident Map

Live Incident Map (Real Data)



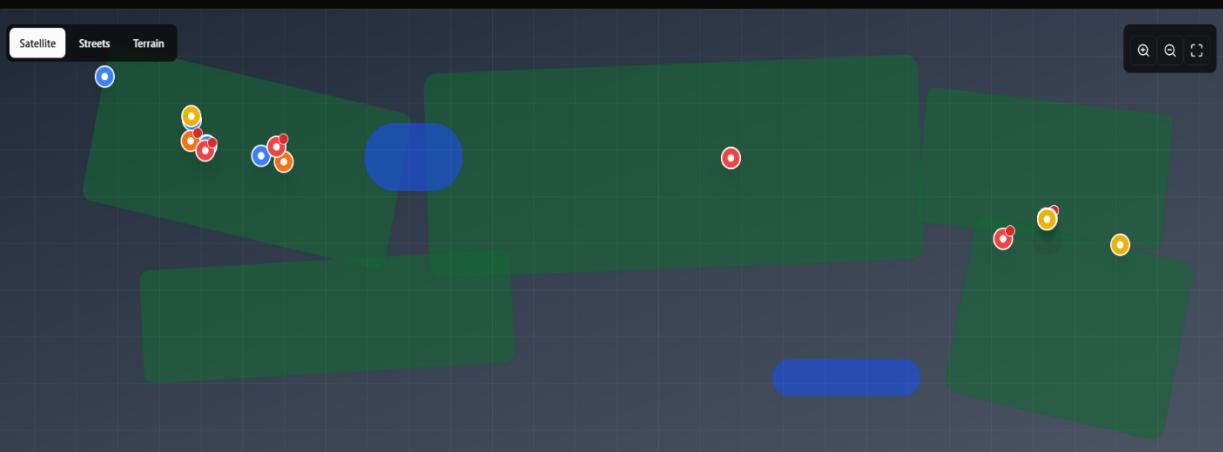
DisasterWatch

Dashboard Map View Analytics Alerts Search incidents... ☰ Filters Settings

Interactive Map

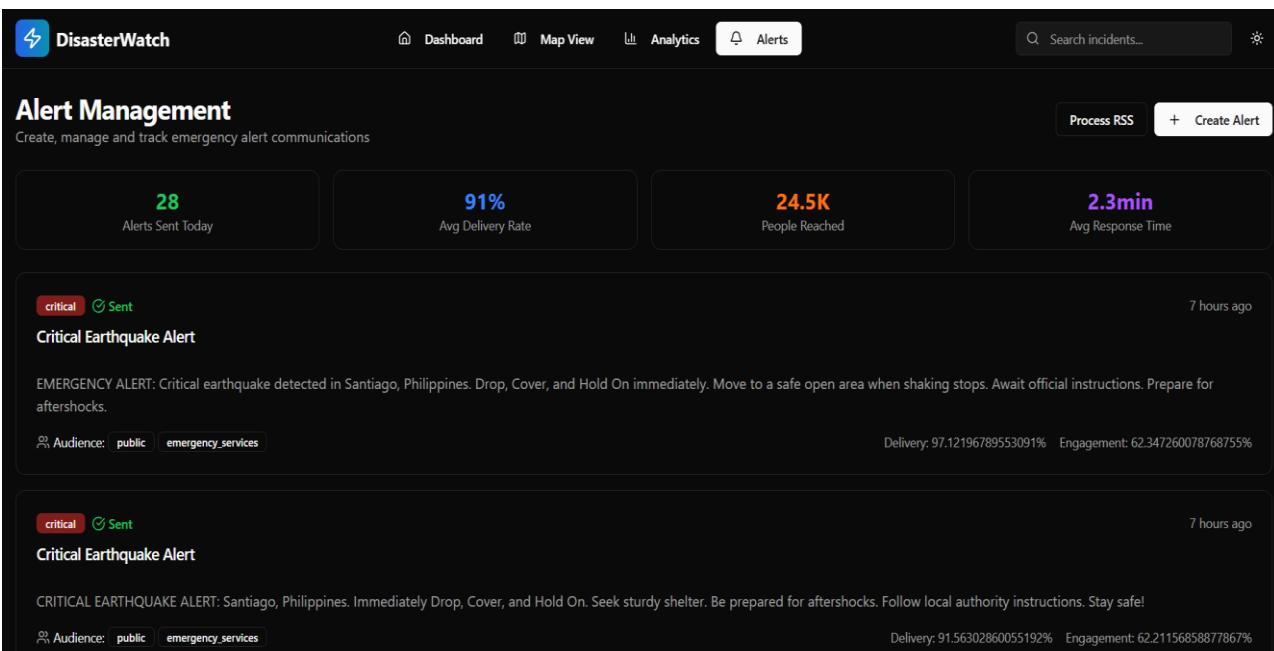
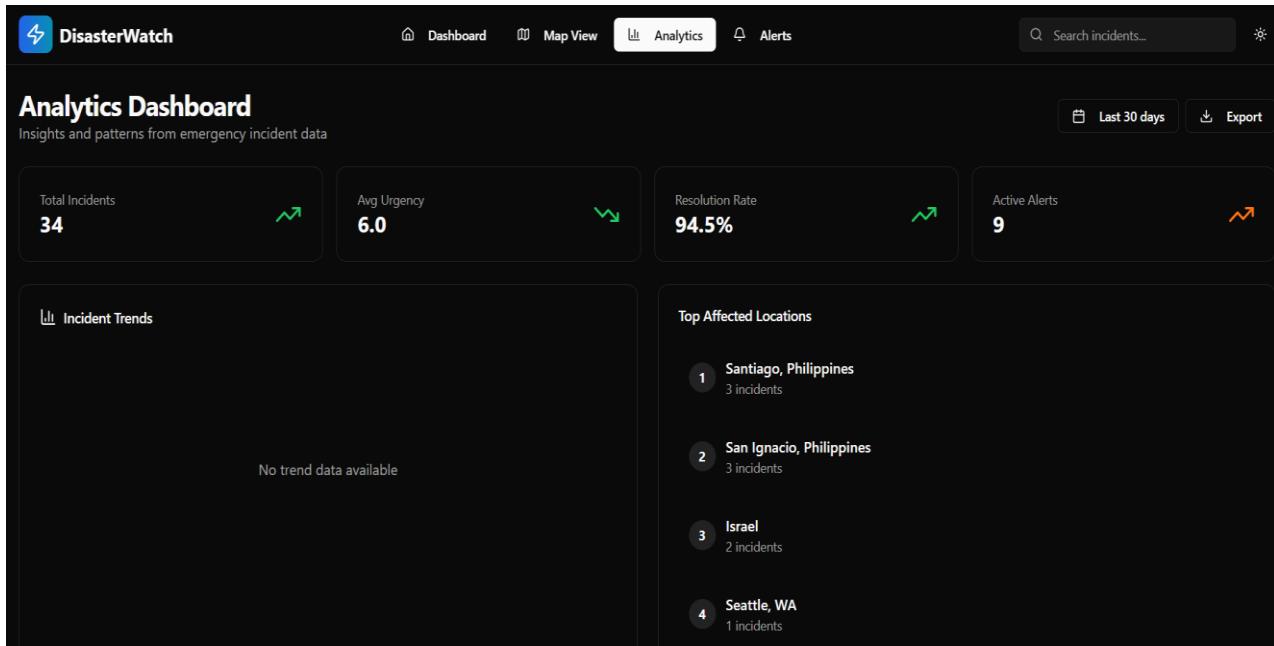
Visualize incidents across geographic regions

Satellite Streets Terrain



21 incidents mapped • Last updated: 10:27:44 AM

● Critical (8) ● Severe (2) ● Moderate (18)



REFERENCES

- [1] Arvandi, Alireza, Jon Rokne, and Reda Alhajj. "Twitter analysis in emergency management: recent research and trends." *Social Network Analysis and Mining* 14, no. 1 (2024): 154.
- [2] Karimiziarani, Mohammadsepehr, and Hamid Moradkhani. "Social response and Disaster management: Insights from twitter data Assimilation on Hurricane Ian." *International journal of disaster risk reduction* 95 (2023): 103865.
- [3] Kabir, Md Yasin, and Sanjay Madria. "A deep learning approach for tweet classification and rescue scheduling for effective disaster management." In *Proceedings of the 27th ACM SIGSPATIAL international conference on advances in geographic information systems*, pp. 269-278. 2019.
- [4] Nair, Meera R., G. R. Ramya, and P. Bagavathi Sivakumar. "Usage and analysis of Twitter during 2015 Chennai flood towards disaster management." *Procedia computer science* 115 (2017): 350-358.
- [5] Shekhar, Himanshu, and Shankar Setty. "Disaster analysis through tweets." In *2015 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, pp. 1719-1723. IEEE, 2015.