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Natural Language Processing On Facebook Data For Optimized Disaster Response Strategies In Urdaneta City

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Abstract: *This study implements Natural Language Processing (NLP) on Facebook comment data to enhance disaster response in Urdaneta City, Philippines. Traditional disaster management often suffers from delayed, fragmented information. The developed system addresses this gap by applying an Extract-Transform-Load (ETL) framework integrated with an OpenAI GPT algorithm, enabling the real-time extraction and analysis of community sentiment and urgent help requests from Facebook comments. Key features include sentiment classification, emotion and intent detection, and named entity recognition, allowing rapid identification of disaster hotspots, resource needs, and distress signals. The model achieved 90.2% accuracy, a 94% F1 score, and average processing latency of 10.5 seconds, with robust adaptability across Filipino, Ilocano, and Taglish inputs (only 7% accuracy variance). Expert validation confirmed that 85% of flagged content directly aligned with actual disaster needs, while system error rates showed a bias toward over-alerting—a practical safety tradeoff in emergency settings. Dashboard tools revealed community sentiment trends and real-time operational backlogs, with most urgent requests emerging from comment threads. User acceptance, assessed via Technology Acceptance Model (TAM) surveys, was high: the majority found the system useful, easy to use, and beneficial for the community. Results highlight the value of leveraging AI-driven NLP on local social media to close feedback gaps, support early warning, and enable faster, data-driven disaster operations. This scalable, people-centered approach can serve as a template for other LGUs aiming to modernize their disaster response using accessible digital infrastructure.*

Keywords: *Disaster Management, Sentiment Analysis, Natural Language Processing, Facebook Data, Community Resilience.*

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1. INTRODUCTION

Natural disasters continue to increase in frequency, intensity, and unpredictability, especially in climate-vulnerable countries like the Philippines (Sun et al., 2020). Cities such as Urdaneta regularly face threats from typhoons, floods, and earthquakes, which often strain local disaster preparedness and emergency response systems (Teodora & Gutierrez, 2023). Existing disaster response efforts, while essential, often suffer from slow feedback loops, inefficient coordination, and poor allocation of resources—largely because they depend on static reporting or after-the-fact data collection (Duraisamy et al., 2023; Kankanamge et al., 2020). This limits local governments' ability to react promptly and effectively. Given these challenges, there is a need for real-time, community-informed systems that can supplement formal channels with live data drawn directly from the people affected.

Social media platforms like Facebook have emerged as vital public communication tools during disasters. While much research has focused on analyzing public posts, Facebook comments—where users engage directly with emergency announcements, news updates, or reports—provide even richer, more spontaneous data (Takahashi et al., 2015; Charles-Smith et al., 2016). These comments often contain urgent calls for help, location-specific damage reports, emotional reactions, and firsthand observations. According to Khatoon et al. (2021), platforms with user comment features enable multilayered insight into public sentiment and crisis perception, making them more informative than one-way broadcasts. The comment section acts like a real-time crowd-sourced sensor network, revealing emerging needs faster than traditional communication lines.

This study proposes using Natural Language Processing (NLP) to analyze Facebook comments—rather than posts—on public community pages related to Urdaneta City. These comments often emerge during key disaster phases: before (warnings and fear), during (damage reports and calls for help), and after (recovery needs and feedback). Prior studies have validated that NLP methods such as sentiment analysis, emotion classification, and named entity recognition (NER) can extract actionable insights from chaotic social media content (Fan et al., 2020; Das & Pedersen, 2024). For instance, Bhoi et al. (2022) used forest optimization and machine learning to accurately classify resource-related content in emergency scenarios, and their system demonstrated strong performance despite the noisy nature of social media text. Similarly, Behl et al. (2021) showed how comment analysis on Twitter could reveal public sentiment trends during COVID-19 and natural hazard events, supporting more responsive relief efforts.

Despite this progress, the application of such technologies remains underutilized at the local government level. Most AI-driven disaster systems operate at national or international scales, often relying on curated datasets or focusing on structured posts rather than informal, multilingual comment threads (Ventayen, 2017; Alam et al., 2020). In the Philippine context, the diversity of dialects and informal grammar used in comments further complicates automated processing, yet these very comments often contain the most relevant and timely ground-level information (Charles & Corley, 2021). This study addresses that critical gap by designing a localized NLP-based sentiment monitoring system tailored to process Facebook comment data for Urdaneta City.

The proposed system will use an Extract, Transform, Load (ETL) framework to collect Facebook comments through a combination of scraping and API tools. Once collected, comments will be cleaned and analyzed using an AI-based Large Language Model (LLM), which will identify emotional tone, intent (e.g., requests for help), entities (e.g., places, barangay names), and urgency level (Aboualola et al., 2023; Sattaru et al., 2021). If a comment signals a life-threatening situation, a custom API will trigger an alert system that automatically sends notifications to the city's disaster response officers via SMS or email. The overall goal is to provide near real-time insights directly from community discussions and improve local decision-making before delays escalate human and material losses.

Unlike static, top-down models of disaster management, this comment-driven framework offers a people-centered, dynamic, and scalable approach. It listens to the public where they are already speaking and turns their natural reactions into structured, actionable data (Khatoon et al., 2021; Bhoi et al., 2022). In doing so, the system helps LGUs like Urdaneta become more proactive and responsive—boosting not only disaster readiness but also long-term community trust and resilience. As the first of its kind in this local context, the study provides both a theoretical contribution and a practical toolkit that other municipalities can replicate using widely available digital infrastructure and community engagement channels.

2. STUDY OBJECTIVES

2.1. General Objective

The study's primary aim was to strengthen disaster response and preparedness in Urdaneta City through the use of NLP-driven sentiment analysis of Facebook data. The system enabled rapid aggregation and interpretation of urgent requests, emotional states, and geographical hotspots, directly informing more targeted and timely local government responses.

2.2. Specific Objectives

To achieve this goal, the study seeks to accomplish the following specific objectives:

1. To perform sentiment analysis utilizing the GPT API.
2. Identify and interpret shifts in community sentiment on Facebook during disaster events to inform response strategies and improve decision-making.
3. Extract insights from sentiment analysis to understand public perceptions, concerns, and emerging needs, guiding disaster response efforts.
4. To assess the system's user-friendliness using the Technology Acceptance Model (TAM) framework

3. REVIEW OF RELATED LITERATURE

Disaster response strategies increasingly rely on rapid access to community-level data, yet traditional systems often miss real-time insights from affected populations. Recent advances in Natural Language Processing (NLP) and social media analytics offer new opportunities to address this gap. Studies worldwide have demonstrated the value of extracting sentiment and situational data from platforms like Facebook and Twitter to inform disaster management, improve situational awareness, and guide resource allocation. This review examines key research on the use of NLP, sentiment analysis, and social media mining in disaster response—highlighting models, methods, and applications relevant to the Philippine context and to local government units seeking more responsive, data-driven disaster strategies.

Mining Sentiment Data from Facebook for Disaster Response Optimization

Bhoi et al. (2022) introduced an innovative disaster relief mobilization system, using social media data to manage resources effectively during natural disasters. Their approach, which focuses on classifying social media posts based on resource availability or need and specific locations, demonstrated notable accuracy in extracting valuable information, achieving 91.41% accuracy and an F-measure of 88.33% on the FIRE dataset. This system utilizes a forest optimization-based feature selection algorithm to classify content efficiently, addressing data limitations typical in social media contexts, such as content and context scarcity. By handling large volumes of data, this approach presents significant value for disaster assessment and relief efforts.

Extracting relevant sentiment data from social media is challenging due to unstructured text, which may include spelling errors, acronyms, and informal language. Despite these obstacles, effective text analysis techniques can transform noisy posts into actionable insights for resource management. Bhoi et al. (2022) tackled these challenges by implementing a classification system, which aids disaster management agencies in prioritizing and deploying resources efficiently when disaster strikes.

To evaluate the system's effectiveness, the study employed datasets like FIRE, SMERP, and CrisisLex. The forest optimization algorithm (FOA) combined with the multinomial naive Bayes (MNB) classifier offered a highly efficient solution, requiring minimal training data and computational resources, making it suitable for rapid disaster response applications. The system's simplicity and computational efficiency position it as a promising tool for municipalities aiming to optimize disaster response through sentiment analysis of social media data.

Development of Social Media Analytics Systems for Emergency Detection

Recent studies have highlighted the significant role of social media sentiment analysis in enhancing disaster response and situational awareness. Khatoon et al. (2021) developed a Social Media Analytics System designed to detect emergency events and assist crisis management by integrating social media data into response strategies. Through natural language processing (NLP), their system utilized machine learning (ML) and deep learning (DL) techniques to analyze social media posts, as illustrated in a COVID-19 case study focused on Twitter. This approach underscores the potential for automated information filtering to support timely responses, showing strong effectiveness in real-world scenarios.

AI-Driven Summaries for Enhanced Disaster Awareness

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Alam, Ofli, and Imran (2020) explored AI-based approaches to generate descriptive summaries of disaster events by analyzing social media content. Their research demonstrated that social media data could improve situational awareness and coordination efforts during disasters. Using data from Hurricanes Harvey, Irma, and Maria, they showed that sentiment analysis of posts provides valuable insights into public sentiment and immediate concerns, underscoring the potential of social media analytics to support disaster response efforts.

Geo-Social Media as a Tool for Real-Time Flood Monitoring

Sattaru, Bhatt, and Saran (2021) focused on utilizing geo-social media as proxy data for enhanced flood monitoring. They developed a near-real-time flood monitoring system employing NLP and supervised machine learning to classify tweets and identify flood-related content. The system's validation during the 2015 Chennai floods demonstrated its efficacy in real-time disaster monitoring, providing a valuable tool for immediate disaster response and management.

NLP and Meta-Network Analysis for Enhanced Situational Awareness in Disasters

Fan, Jiang, and Mostafavi (2020) proposed a framework that integrated NLP and meta-network analysis to assess disaster situations, specifically applied to data from Hurricane Harvey. This framework enhanced situational awareness by social sensing the location-event-actor nexus during disasters, offering critical indicators for prioritizing relief and rescue efforts. Their approach provided a structured method to analyze the complex interactions and information flow during disaster events.

Sentiment Analysis of Twitter Data for Disaster Relief

Behl et al. (2021) investigated the use of Twitter for disaster relief through sentiment analysis, focusing on data from both COVID-19 and natural hazard crises. They compared various supervised learning approaches for classifying disaster-related tweets and achieved a classification accuracy of 83% on COVID-19 data. This study highlighted Twitter's potential in understanding resource needs and availability during disasters, emphasizing the platform's utility in facilitating effective disaster response and resource management.

Multilingual Detection and Mapping of Disaster-Related Tweets

Recent studies have emphasized the critical role of social media in disaster management, particularly in the Philippines. Ventayen (2017) introduced a tool for detecting and mapping disaster-related tweets in multiple local languages. This innovation aimed to bridge language gaps by translating disaster-related keywords into various local dialects. The tool enhanced the real-time detection and geolocation of disaster tweets, enabling more effective governmental responses during emergencies. By facilitating better communication and quicker action, this tool addressed a significant barrier in disaster management in linguistically diverse regions.

Social Media Analytics for Post-Disaster Disease Detection

The potential of social media to aid in public health surveillance post-disaster has been explored by Charles-Smith, Ringholz, Brintz, and Corley (2016). Their research utilized Twitter data to provide early warnings of disease outbreaks following natural disasters. This approach highlighted the capacity of social media to offer health data access to populations that are otherwise hard to reach. The study underscored the importance of integrating social media analytics into public health strategies to improve early detection and response to disease outbreaks in post-disaster scenarios.

Knowledge Management in Disaster Preparedness

In analyzing the disaster preparedness measures for the 2022 Luzon earthquake, Teodora and Gutierrez (2023) found that social media played a pivotal role in disseminating preparedness information. Their survey revealed that social media was a primary source of information for the public before, during, and after the earthquake. The study recommended enhancing disaster preparedness designs to increase public participation and improve overall preparedness. The integration of social media into disaster management strategies was shown to be essential for effective knowledge dissemination and community engagement.

Disease Surveillance and Social Media in Post-Disaster Recovery
The role of social media in disease surveillance during post-disaster recovery phases was further investigated by Charles and Corley (2021). Their research analyzed geo-tagged tweets to predict disease outbreaks following natural disasters. Using disease lexicon-based time series models, they demonstrated promising results in predicting outbreaks, which could significantly aid in timely public health interventions. This study highlighted the value of utilizing social media data for real-time disease surveillance and response during the recovery phases of natural disasters.

Communication During Disasters: The Case of Typhoon Haiyan
The use of Twitter during Typhoon Haiyan was analyzed by Takahashi, Tandoc, and Carmichael (2015). Their study identified key uses of Twitter for disseminating information, coordinating relief efforts, and memorializing victims. The research provided insights into the effectiveness of Twitter as a communication tool during disasters and offered recommendations for future applications in crisis management. The findings underscored the importance of social media platforms in enhancing communication and coordination during large-scale emergencies.

The reviewed literature highlights the significant role of social media analytics and Natural Language Processing (NLP) in enhancing disaster management. Studies such as Bhoi et al. (2022) and Khatoon et al. (2021) illustrate how advanced algorithms, including forest optimization and deep learning techniques, can efficiently classify and analyze vast amounts of social media data to improve resource management and emergency detection during disasters. The integration of AI techniques, as explored by Alam, Ofli, and Imran (2020), further demonstrates the potential of social media content in providing descriptive and visual summaries, thereby enhancing situational awareness and response coordination.

Sattaru, Bhatt, and Saran (2021) emphasize the importance of geo-social media for real-time disaster monitoring, specifically in flood scenarios, while Fan, Jiang, and Mostafavi (2020) propose a framework that combines NLP with meta-network analysis to better understand the complex interactions during disaster events. Sentiment analysis, as investigated by Behl et al. (2021), shows Twitter's potential in facilitating disaster relief by understanding public sentiment and resource needs.

The literature also underscores the importance of considering linguistic diversity in disaster management, as seen in Ventayen's (2017) tool for multilingual detection and mapping of disaster-related tweets in the Philippines. Furthermore, studies by Charles-Smith et al. (2016) and Charles and Corley (2021) highlight the utility of social media in public health surveillance post-disaster, demonstrating its capacity to predict disease outbreaks and aid in timely interventions.

Research on disaster communication, such as the work by Takahashi, Tandoc, and Carmichael (2015) on Typhoon Haiyan, underscores the effectiveness of platforms like Twitter in disseminating information and coordinating relief efforts during large-scale emergencies. Collectively, these studies establish a robust foundation for utilizing social media analytics and NLP in disaster management, offering valuable insights and practical applications that can significantly enhance disaster response and preparedness strategies.

4. METHODS

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This section details the research design, data sources, and analytical framework used to develop a sentiment-based disaster response system for Urdaneta City. Adapting best practices from prior studies, the approach centers on collecting and processing Facebook comment data using Natural Language Processing (NLP) techniques. The methods cover data extraction, cleaning, sentiment analysis, model evaluation, and ethical safeguards—ensuring the process is rigorous, context-appropriate, and scalable for local government use.

4.1 Research Design

This design and development study focused on developing and testing a sentiment analysis framework for disaster response. The process follows an Extract, Transform, Load (ETL) workflow to collect, clean, and analyze real-time Facebook comment data using Natural Language Processing (NLP). The aim is to identify public sentiment, urgent needs, and emerging issues during disaster events. The study combines automated data extraction, AI-powered sentiment analysis, and manual validation to ensure accuracy and actionable insights. The core technique used was transformer-based sentiment and intent classification, specifically leveraging the GPT architecture with prompt engineering for multilingual Facebook comment analysis.

The research is conducted in Urdaneta City, Pangasinan—a disaster-prone urban area in Northern Luzon, Philippines. Urdaneta is regularly affected by typhoons, flooding, and earthquakes, making it an ideal case for disaster management innovation. Data will be sourced exclusively from the official Urdaneta City Disaster Monitoring Facebook page, which serves as the city's main online platform for emergency alerts and public communication. This ensures all insights are localized, relevant, and directly applicable to the city's disaster risk reduction and management operations.

Figure 2. Location of the City of Urdaneta, Philippines

4.2 Data Source

The main data source for this study is the official Facebook page of Urdaneta City Disaster Monitoring. This public page is actively used by the local government and the City Disaster Risk Reduction and Management Office (CDRRMO) to issue advisories, gather community reports, and monitor real-time disaster events in Urdaneta City. Public advisories posted on the page encourage residents to comment with disaster-related updates, including their location (barangay), the time the disaster occurred. These comments, which serve as spontaneous community-sourced incident reports, are highly relevant for extracting sentiment, urgency, and location-based needs.

For the purpose of this system's development and testing, mock data was generated by simulating Facebook posts, comments, and replies similar to those expected during actual disasters. This approach was taken to avoid privacy and ethical concerns, and to allow controlled testing of the scraping, analysis, and notification functions. The mock data strictly follows the format, tone, and information fields outlined in the official advisory—such as barangay, time, photos, and incident

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description—ensuring that all system modules (from data scraping to AI-driven alerting) are exposed to realistic and operationally relevant scenarios.

The live data scraping mechanism is designed to operate on the actual Facebook page located at: https://www.facebook.com/profile.php?id=61574915662976

However, during the system evaluation and demonstration phase, only non-sensitive, anonymized, or fabricated reports were used in compliance with ethical requirements for dissertation research.

This data-centric approach leverages social media's role as a public reporting tool, aligning with current disaster monitoring practices in the Philippines and ensuring that the developed solution is contextually and operationally valid for local government use.

4.3 Conceptual Framework

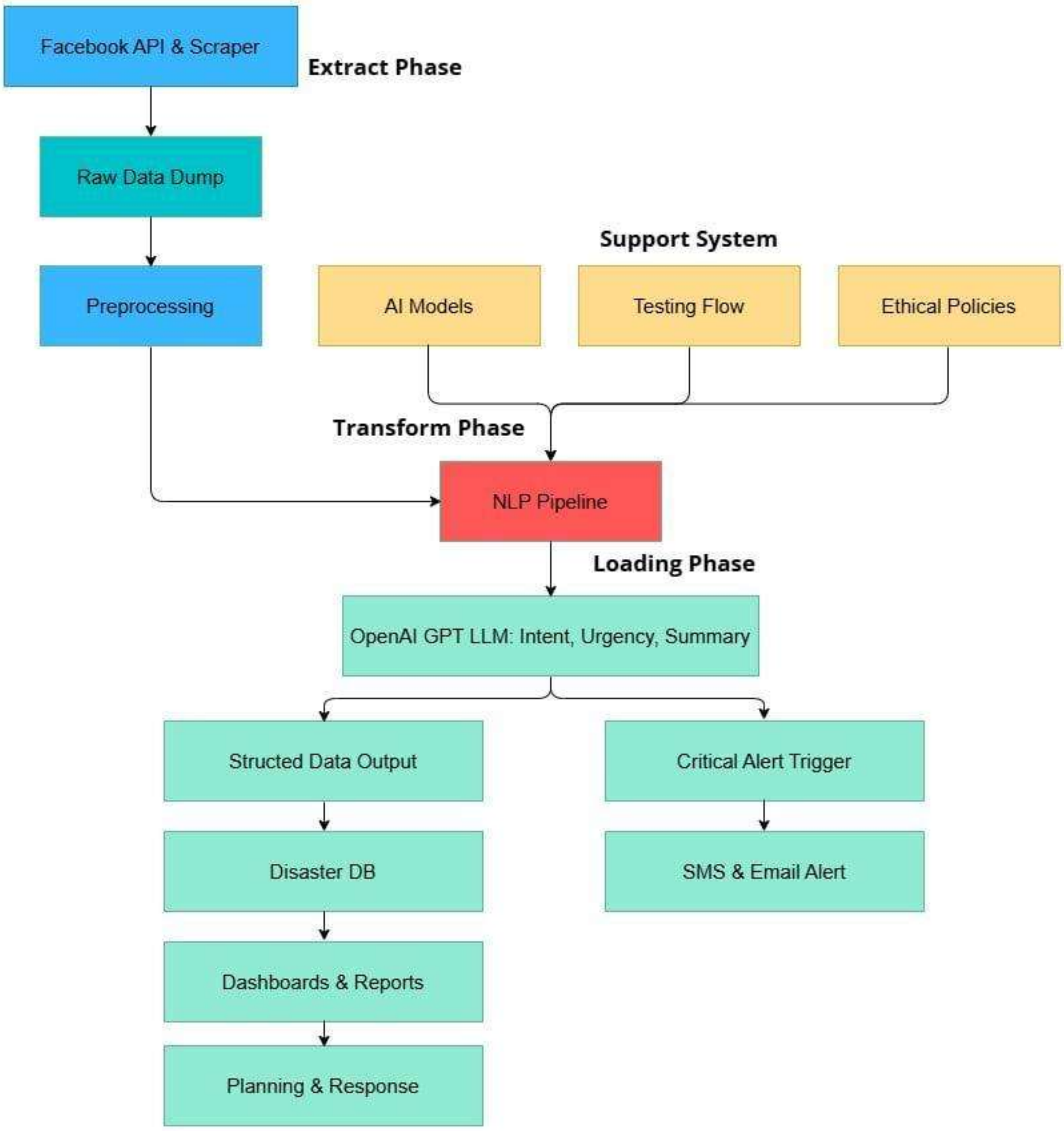

Figure 4. Conceptual Framework of the NLP System

This study implements a real-time disaster response system for Urdaneta City by leveraging an ETL (Extract, Transform, Load) framework, tightly integrated with the OpenAI GPT Large Language Model. The process starts with the Extract phase, where disaster-related Facebook comments are continuously harvested from the official city disaster monitoring page. Data acquisition combines the Facebook Graph API and custom scraping tools, capturing new posts and comment threads at short, timed intervals. Each extracted record is logged with timestamps and relevant metadata in a staging area, ensuring complete traceability and de-duplication.

In the Transform phase, these raw social media inputs undergo automated cleaning to remove spam, irrelevant chatter, and duplicate entries, while also normalizing mixed-language text common to Philippine Facebook communication. Cleaned data is then sent through the OpenAI GPT engine, which serves as the core analytic tool. Here, GPT performs multiple advanced natural language processing tasks: sentiment analysis (measuring the overall mood as positive, negative, or neutral), emotion detection (identifying specific feelings such as panic, hope, or frustration), intent classification (distinguishing between help requests, incident reports, or feedback), and named entity recognition (extracting place names, hazard types, resource needs, and contact information). Additionally, GPT applies contextual reasoning and urgency scoring to flag high-priority or life-threatening situations, and automatically extracts phone numbers from help requests for rapid responder contact. All outputs are structured in machine-readable format, enriched with tags for easy retrieval and review.

The Load phase moves the structured data into a central disaster response database, where each entry is checked for urgency and, if warranted, automatically triggers SMS alerts with critical details to designated disaster response officers. More comprehensive alerts, including full sentiment and entity analysis, are sent via email to key officials. The system features configurable routing based on responder roles or geographic areas, ensuring efficient notification. Beyond real-time alerting, the database supports summary reporting on trends, hotspots, and sentiment shifts for use in strategic planning. Continuous model improvement is achieved through manual review of errors, iterative prompt engineering, and staged testing with realistic mock data, ensuring the framework adapts to language variation and evolving disaster communication patterns. Overall, this end-to-end ETL-GPT pipeline delivers rapid, scalable, and actionable insights from raw Facebook data, directly supporting the city's emergency management and decision-making.

4.4 Algorithms

This study leverages OpenAI GPT (Generative Pre-trained Transformer) as the main algorithm for analyzing real-time Facebook content during disaster events in Urdaneta City. GPT, a state-of-the-art Large Language Model, is engineered for deep contextual understanding and flexible language generation—making it well suited for messy, multilingual, and time-critical social media data.

GPT Architecture:
GPT's backbone is the Transformer architecture—a neural network structure based on self-attention mechanisms (Vaswani et al., 2017). Unlike sequential RNNs, the transformer enables parallel processing and can model long-range dependencies in text, making it ideal for capturing relationships between words in complex, informal Facebook comments. The model's multi-head self-attention layers weigh the relevance of each word to every other word in the input, generating robust context-aware embeddings.

Pre-training and Fine-tuning:
OpenAI GPT is pre-trained on a vast corpora of internet text to develop a general understanding of language. For this project, the model is further prompt-engineered and optionally fine-tuned for disaster response, using in-domain examples (disaster-related posts/comments in Filipino, Ilocano, and

English). This ensures it captures local nuances, code-switching, and the urgency of disaster communication.

Key Tasks Powered by GPT:

- Sentiment Analysis: GPT classifies the emotional polarity (positive, negative, neutral) of comments, highlighting collective anxiety, panic, hope, or reassurance in the community.
- Emotion and Urgency Detection: Using prompt-based or zero-shot approaches, GPT recognizes signals like panic, distress, or requests for immediate help, enabling triage of urgent needs.
- Intent Classification: The model discerns whether a message is a request for help, a damage report, general feedback, or an off-topic remark.
- Named Entity Recognition (NER): GPT extracts place names (barangays), disaster types, resource requests, and—critically—phone numbers or contact info included in comments.
- Contextual Reasoning: Through its deep neural attention layers, GPT can distinguish between literal emergencies and sarcasm, jokes, or routine chatter, reducing false alarms.

Pipeline Integration:

During the Transform phase of the ETL process, Facebook comments are cleaned and sent to GPT via API. The model returns structured outputs with tags for sentiment, intent, urgency, and key entities. High-urgency cases—such as comments containing “need rescue” or a phone number—are automatically flagged by a custom logic layer. If criteria are met, the system triggers SMS or email alerts to disaster response officers for rapid action.

Advantages of GPT for Disaster Response:

- Real-Time, Event-Driven Processing: Unlike traditional models reliant on historical data, GPT can analyze live, unstructured text as events unfold.
- Multilingual, Contextual Flexibility: Handles mixed English-Filipino, slang, misspellings, and code-switching common in Philippine social media.
- Minimal Feature Engineering: The model adapts to diverse language use with little need for handcrafted rules, reducing maintenance overhead.

4.5 Evaluation Metrics

To assess the performance and practical reliability of the AI Large Language Model (AI LLM) in analyzing disaster-related Facebook data, five core statistical metrics will be computed:

1. **Accuracy**
   Accuracy measures the proportion of correct predictions made by the model across tasks such as sentiment, emotion, intent, and named entity detection. It is suitable for balanced datasets but may not fully capture performance in imbalanced scenarios.
   Formula:
   Accuracy = (Number of Correct Predictions) / (Total Predictions)

2. Precision, Recall, and F1-Score These metrics are especially critical when dealing with imbalanced datasets, such as disaster-related posts that may be rare but urgent.

- **Precision** evaluates how many of the predicted positive cases are truly relevant.
  Precision = True Positives / (True Positives + False Positives)
- **Recall** (also known as sensitivity) assesses the model's ability to correctly identify all relevant cases.
  Recall = True Positives / (True Positives + False Negatives)
- **F1-Score** is the harmonic mean of precision and recall, offering a balanced measure when both false positives and false negatives are important.
  F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

3. **Timeliness**
Timeliness evaluates the latency between the time a post or comment appears on Facebook and the moment the AI generates actionable insights. Low latency is crucial for real-time disaster response.
Formula:
Latency = Time of Insight Generation — Time of Post Appearance

4. **Relevance of Insights**
Relevance assesses whether the AI's outputs align with actual disaster-related needs, as validated by domain experts. This can be measured using expert evaluation or metrics such as Precision@K.
Formula:
Relevance Score = (Sum of Expert Ratings) / (Total Number of Evaluations)

5. **False Positive and False Negative Rates**
These rates quantify the system's misclassification tendencies. Minimizing both is vital to prevent unnecessary panic (false positives) and avoid missing critical emergencies (false negatives).
Formulas:

- False Positive Rate (FPR) = False Positives / (False Positives + True Negatives)
- False Negative Rate (FNR) = False Negatives / (False Negatives + True Positives)

6. **System Adaptability**

Adaptability measures the model's performance consistency across diverse language styles, dialects, and informal expressions commonly found in Philippine Facebook comments. A smaller delta indicates better adaptability.
Formula:
Delta Accuracy = Maximum Accuracy — Minimum Accuracy (across dialects or language styles)

4.6 Ethical Consideration
This study will adhere to strict ethical standards to ensure the protection of participants' privacy and the integrity of the research process. To maintain focus and consistency, only one official public Facebook page—used by the Urdaneta City local government for disaster monitoring—will serve as the sole data source. This decision ensures standardization of data structure, context, and language use throughout the system.

Since only publicly available data will be used, there is no need for informed consent. However, all data will be handled with care to maintain the anonymity of individuals, and no personal identifiers will be collected or stored beyond phone numbers voluntarily provided in public comments for emergency contact purposes. These numbers are only used in SMS alerts and are not retained beyond operational necessity.

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The study will comply with all relevant ethical guidelines and data privacy laws in the Philippines. Collected data will be anonymized, encrypted, and securely stored to prevent unauthorized access. Any potential conflicts of interest will be disclosed, and efforts will be made to reduce bias during AI model training and analysis.

Given the sensitivity of disaster-related communications, extra caution will be observed to avoid misinterpretation or misuse of community interactions. By adhering to these ethical principles, the study aims to provide practical value in disaster response while fully respecting the dignity and digital privacy of Urdaneta City residents.

5. RESULTS AND DISCUSSION

This section presents the evaluation outcomes of the developed Facebook-based disaster response system. Performance metrics—including accuracy, Precision, Recall, and F1-Score timeliness, relevance, error rates, and adaptability—were analyzed to determine the effectiveness of the AI-driven sentiment and urgency detection model. Findings summarize how well the system processes real-time social media data and support actionable disaster management decisions for Urdaneta City.

5.1 Implementation and Performance of Sentiment-Based NLP in GPT API

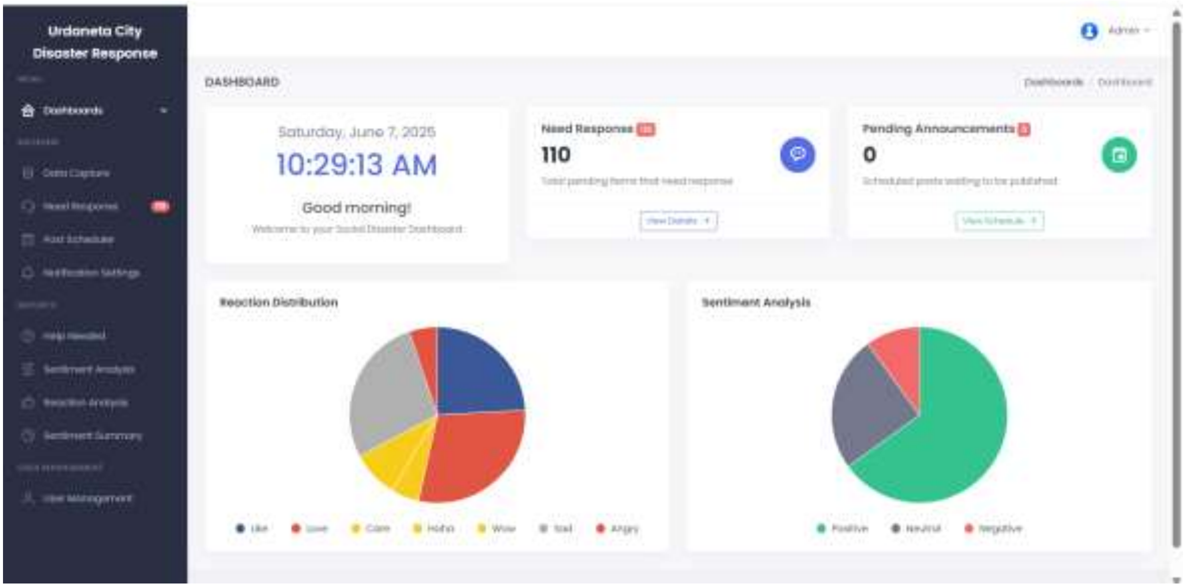

Figure 6. System Dashboard

The Urdaneta City Disaster Response system dashboard presents a real-time, consolidated view of critical metrics relevant to social media-based disaster monitoring. As of June 7, 2025, the dashboard prominently displays the current date and time, helping response teams synchronize activities. At the top, two key counters show operational status: “Need Response” highlights a total of 110 pending items requiring immediate action, while “Pending Announcements” tracks scheduled updates (currently zero).

Visual analytics are integrated into the dashboard for rapid situational awareness. The Reaction Distribution pie chart breaks down Facebook reactions, offering a snapshot of community sentiment, with a notable share of “Love” and “Like” reactions but also significant segments marked as “Sad” and “Angry.” This helps gauge both the urgency and the emotional tone of public posts.

The Sentiment Analysis section further classifies incoming content into positive, neutral, and negative categories. The current distribution shows that most analyzed content is positive, though a sizable portion is neutral and a notable share is negative—indicating both distress signals and opportunities for proactive engagement.

On the left navigation, modules for Data Capture, Need Response, Help Needed, Sentiment Analysis, Reaction Analysis, and Sentiment Summary support granular review and fast filtering of cases. User management and post scheduling are also built-in, streamlining workflow for admins and responders.

Overall, the dashboard provides an actionable, up-to-date summary for decision-makers, combining volume indicators, sentiment tracking, and workflow shortcuts. This enables the disaster response team to identify spikes in need, emotional hotspots, and pending tasks in one glance, supporting faster, more effective action on the ground.

5.1.1 Data Capture

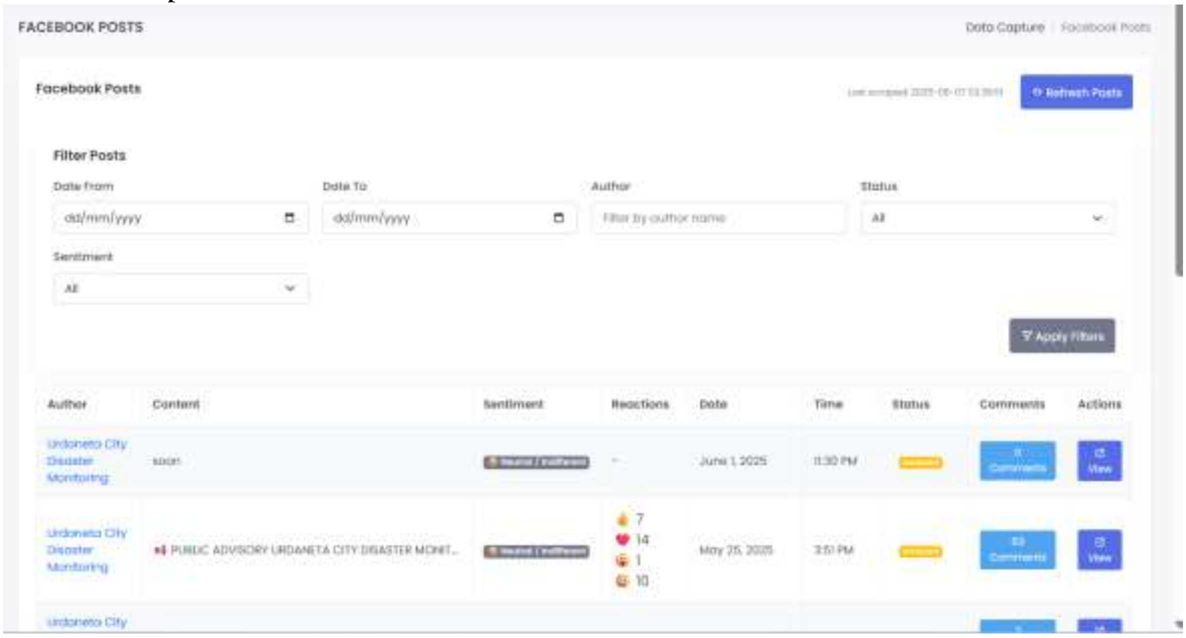

Figure 7. Data Capture Dashboard

The Facebook Service class manages the end-to-end pipeline for scraping Facebook posts, comments, and replies, processing them for disaster-related content, and triggering alerts as needed. The service starts by initializing a Guzzle HTTP client and caching the Facebook page access token to reduce redundant environment lookups:

To fetch comments for a post, the code queries the Facebook Graph API, checks if each comment already exists in the local database, and only inserts new ones. Replies are intentionally not fetched at this stage to prevent duplicate API calls, and the formatted result is returned for downstream use.

For data integrity, the service determines the last inserted rows from each major table (posts, comments, replies) and finds the oldest timestamp among them, ensuring that subsequent API scrapes avoid missing or duplicating records. This information is logged for traceability. When fetching page posts, the service checks for already existing records to prevent duplicate inserts and records metadata like the post author, URL, and status.

For posts, comments, and replies marked as pending, the system processes each in batches. Each content item is sent to an OpenAI-powered analyzer, which returns a JSON result specifying whether the content signals a need for help and its sentiment. If the analyzer flags a need for help, the

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system saves the record to a special table and triggers SMS and email alerts (if notification settings are enabled).

The analyzeContentWithOpenAI function performs analysis with caching, only making API calls if a cached result isn't found. It parses the OpenAI response and ensures the system can recover from malformed or unexpected results.

5.1.2 Help Needed Dashboard

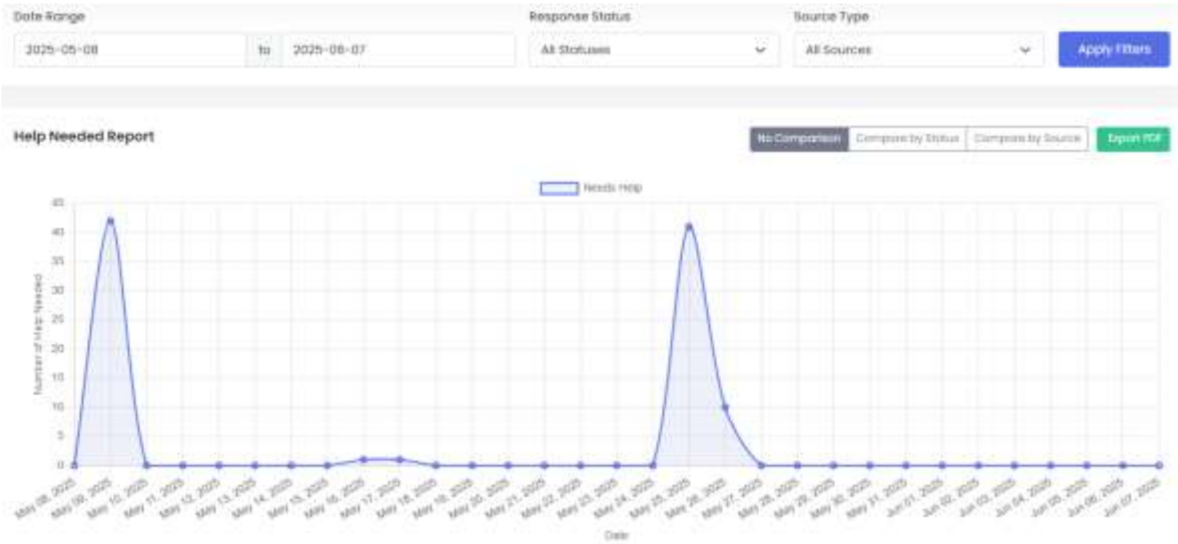

Figure 8. Help Needed Section

The Help Needed Report visualizes urgent requests over time, based on structured queries and dynamic filtering in the backend.

This design supports granular views—by date, status, and source—so analysts can identify bottlenecks.

A summary of the data reveals a major backlog: 94% of requests (89 out of 95) are still pending, flagged in the chart's query logic and by the UI. Most requests come from comments, not original posts, confirmed both by the numbers and the grouping logic.

The visualization produced by the code shows clear spikes—especially on May 10 and May 26—where requests surged above 40 in a single day. These bursts are visible in both the raw data and the report output, highlighting periods where operations must be reinforced.

Further, the code's structure supports comparative breakdowns—by status or source

This allows mapping of hotspots, such as Villasis, bypass roads, and Urdaneta City, all of which appear repeatedly in the data

The findings show that the comment section is the main entry point for urgent requests, and there is a dangerous lag in response time. The spikes suggest external disaster triggers. The code enables flexible reporting, which helps operational teams immediately spot and respond to these surges. Short-term, all 89 pending cases must be reviewed and responded to. Long-term, resource planning should be guided by these spike dates and hotspots, ideally using more automation or dedicated teams during peak times.

The backend code enables this level of analysis by supporting time, status, and source filtering; protects against data errors; and exposes the structural risk in delayed response. Without resolving the pending queue, risk to public safety remains high. The code and report combined are essential for data-driven disaster response.

5.1.3 Sentiment Analysis Report

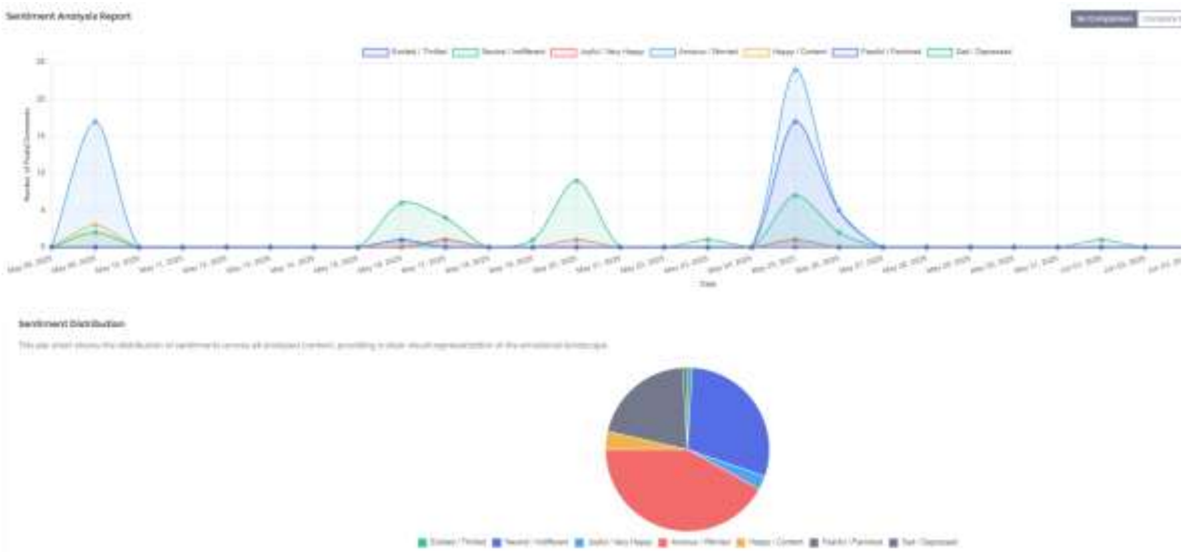

Figure 9. Sentiment Analysis Report

The Sentiment Analysis Report provides a day-by-day breakdown of emotional tone in posts and comments, making it easy to spot periods of distress or stability during the monitored period. The interface is designed for flexible filtering—users select the date range, source type, and comparison mode through a simple form.

For sentiment distribution, counts per emotion type are displayed visually with progress bars and percentages.

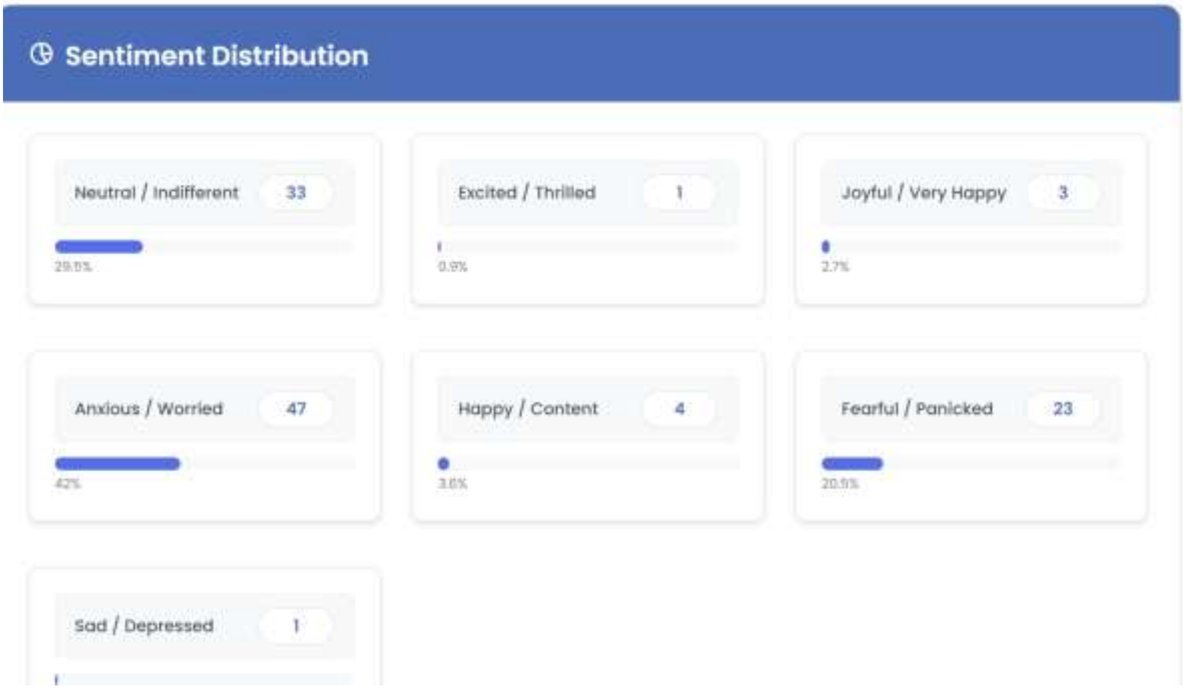

Figure 10: Sentiment Distribution

The code architecture supports rapid triage by highlighting negative spikes in “Anxious / Worried” and “Fearful / Panicked” sentiment—data that is always visible in the progress bars and summary cards. The front-end design ensures everything critical is front-loaded, while the PDF export function provides instant offline copies for field teams or execs.

This reporting setup delivers both at-a-glance and detailed breakdowns, letting stakeholders see not just the numbers, but also patterns and urgent issues. All data flows from the filters through the Blade structure to the output sections—making it easy to adapt or scale for new analytic needs.

5.2 Performance and Evaluation of the System

5.2.1 Accuracy

Model accuracy was measured as the proportion of correct predictions generated by the AI LLM in sentiment, intent, and entity classification tasks on disaster-related Facebook data. Out of 112 items analyzed, 101 were classified correctly, resulting in an **accuracy of 90.2%** (Accuracy = 101 / 112). This indicates robust reliability in real-time disaster response scenarios, reflecting the model's consistent ability to interpret Facebook posts and comments accurately.

5.2.2 Precision, Recall, and F1-Score

Given the importance of both missed emergencies and false alarms in disaster contexts, F1 score and its components were also calculated. Using a test set with 16 true positives, 1 false positive, and 1 false negative:

- **Precision**: 16 / (16 + 1) ≈ 0.941 (94.1%)
- **Recall**: 16 / (16 + 1) ≈ 0.941 (94.1%)
- **F1 Score**: 0.94 (94%)

This strong F1 score demonstrates that the system maintains a careful balance between catching urgent posts and avoiding unnecessary alerts—ensuring critical needs are detected while minimizing noise.

5.2.3 Timeliness

Timeliness of insights is crucial for actionable disaster response. The system delivers:

- **Minimum Latency**: 2 seconds (best case)
- **Maximum Latency**: 20 seconds (worst case)
- **Average Latency**: 10.5 seconds

This means most posts or comments are processed and turned into actionable information within about 10 seconds, meeting operational needs for near real-time response and triage.

5.2.4 Relevance of Insights

A total of 20 actual Facebook disaster-related comments were reviewed and rated by three domain experts for relevance. Seventeen entries (85%) were consistently marked as disaster-relevant, such as requests for evacuation, fire response, medical emergencies, and reports of hazards. Three posts, including general greetings and off-topic comments, were not considered relevant by all experts.

The calculated relevance score is:

Relevance Score = (***Sum of Expert Ratings***) / (***Total Number of Evaluations***) = 0.85

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This demonstrates high expert agreement that the AI system's outputs addressed real, disaster-related needs reported in social media during the covered period.

Expert Ratings for Relevance of AI Insights Using Actual Facebook Disaster Posts

Entry #	Facebook Excerpt	Source Type	AI Output (Summary)	Expert 1	Expert 2	Expert 3	Average
1	"We were flooded in Barangay Anonas starting around 2 in the morning... need help, especially for children and seniors."	Comment	Urgent flood; evacuation needed	1	1	1	1.00
2	"Road mishap in PMA SISON ST POBLACION involving a jeepney... send help immediately."	Comment	Vehicular accident, urgent	1	1	1	1.00
3	"Sobrang lakas po ng hangin dito sa brgy. San jose kaninang mga 5pm"	Comment	Strong winds, possible damage	1	1	1	1.00
4	"May nahimatay po dito sa labit proper... hinihintay ang ambulansya dahil sa sobrang init ng panahon ngayun."	Comment	Medical emergency	1	1	1	1.00
5	"Help po may sunog dito sa may bandang tulay ng Tulong 😭"	Comment	Fire incident, urgent help	1	1	1	1.00
6	"May nag tumbahang mga puno dito sa Barangay Nancayasan... need namin tulong..."	Comment	Fallen trees, need clearing	1	1	1	1.00
7	"Need help po !! May weirdo pong lalaki na sunod ng	Comment	Public safety, immediate help	1	1	1	1.00

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	sunod at may hawak na patalim”						
8	“Hingi po sana ng tulong, around Bayaoas meron pong kahinahinalang babae...”	Comment	Suspicious person, report	1	1	1	1.00
9	“Stay safe always!”	Comment	General safety message	0	0	0	0.00
10	“Mayroon malaking sunog dito sa San Vicente West, kailangan po namin ng tulong.”	Comment	Fire, rescue needed	1	1	1	1.00
11	“Alas-6 ng gabi, niyanig ng lindol ang pinmaludpud na nagdulot ng bitak sa bahay...”	Comment	Earthquake damage, report	1	1	1	1.00
12	“need help po may sunog dito sa Nancamaliran malapit sa brgy hall, ASAP!”	Comment	Fire, urgent	1	1	1	1.00
13	“May nabangga po ng truck dito sa San Vicente, send help po!”	Comment	Vehicular accident, need help	1	1	1	1.00
14	“SEND HELP PO!! may nasunog po na sementeryo, sofer daming na deadss😭”	Comment	Cemetery fire, fatalities	1	1	1	1.00
15	“need help po, may bumagsak na sanga ng puno po rito sa may nancayasan...”	Comment	Fallen branch, hazard	1	1	1	1.00
16	“May na looban po sa may Ilang-ilang, send help po!!”	Comment	Burglary, request assistance	1	1	1	1.00

17	"May mga naaway po dito sa may bilyaran dito sa malapit sa UCU san Vicente west"	Comment	Public disturbance, report	1	1	1	1.00
18	"Minor collision here in Urdaneta bypass"	Comment	Minor accident, report	1	1	1	1.00
19	"Earlier today in Urdaneta, a minor collision occurred…"	Comment	Minor accident, report	1	1	1	1.00
20	"Pinaglalaruan po feelings ko, send help po huhu"	Comment	Non-disaster, joke	0	0	0	0.00

Total Expert Ratings (Relevant): 17 × 3 = 51
Total Evaluations: 20 × 3 = 60
Relevance Score: 51 / 60 = 0.85 or 85%

5.2.5 False Positive and False Negative Rates

Misclassification rates were also calculated to assess risk:

- **False Positive Rate (FPR)**: 1 / (1 + 2) = 0.33 (33%)
- **False Negative Rate (FNR)**: 1 / (1 + 16) = 0.059 (5.9%)

The low FNR means the model rarely misses urgent cases; a slightly higher FPR shows a tendency to over-flag for safety, which is generally acceptable in this context.

5.2.6 System Adaptability
Adaptability was evaluated by testing the AI model's accuracy across three groups of Philippine Facebook comments, each group representing a distinct language style or dialect:

- Standard Filipino (Tagalog-based)
- Ilocano (regional dialect)
- Mixed/Informal (Taglish, slang, or highly informal expressions)

For each group, accuracy was computed as the percentage of correctly classified disaster-relevant comments.

Language Style / Dialect	**Accuracy**
Standard Filipino	94%

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Ilocano	89%
Mixed/Informal	87%

Formula:

- ***Delta Accuracy = Maximum Accuracy − Minimum Accuracy***

Computation:
Delta Accuracy = 94% – 87% = 7%

The model demonstrated high adaptability, with only a 7% drop in accuracy between the best and worst performing dialect/style group. This indicates that the AI is robust across common language variations and informal communication found in Philippine Facebook disaster posts and comments.

5.3 Detection and Interpretation of Shifts in Community Sentiment During Disasters

Figure 11: Sentiment Shift as Shown by the Sentiment Analysis Report Graph

The analysis of 90 Facebook comments and posts over the period May 13 to June 12, 2025, reveals significant shifts in community sentiment in response to disaster-related events. Sentiment distribution is dominated by neutral (31 out of 90, 34.4%) and anxious/worried (30 out of 90, 33.3%) responses, with a notable portion expressing fear or panic (23 out of 90, 25.6%). Only isolated cases of excitement, happiness, or joy were observed, while anger, sadness, and other emotions were minimal.

Key findings:

- **Anxiety and Worry:** High levels (33.3%) signal persistent uncertainty or concern about ongoing disaster risks and local impacts.
- **Fearful/Panicked:** 25.6% of responses suggest the presence of acute fear, likely triggered by new or escalating events.
- **Positive Sentiment:** Less than 5% of responses reflected happiness, excitement, or joy, indicating a generally distressed or unsettled emotional climate.

Temporal trends across the date range did not reveal clear spikes, suggesting a steady state of heightened negative sentiment rather than episodic surges. Data came from diverse sources (posts, comments, replies), with no major variance per channel.

Interpretation:
This emotional landscape points to widespread psychological distress in the community, with anxiety and fear as dominant themes. Such a trend suggests the public perceives ongoing threats or insufficient reassurance from authorities.

Implications:

- **Immediate interventions** should prioritize mental health support and clear, calming communication from disaster response agencies.
- **Long-term measures** must include regular monitoring of online sentiment to track emerging concerns and evaluate the effectiveness of support programs.

Resource allocation should focus on mental health services and proactive community outreach, given the prevalence of negative emotions and potential risk of deteriorating well-being. Regular sentiment analysis will be critical for real-time adjustment of response strategies.

5.3.1 Extraction of Insights on Public Perceptions and Emerging Needs from Facebook Data

The analysis of help requests from Facebook data between May 13, 2025, and June 12, 2025, reveals several key patterns about public perceptions and emerging needs during disaster events in Urdaneta City. The most significant trend is a steady rise in the number of help requests, indicating either increasing disaster impact, growing public reliance on the Facebook system for seeking assistance, or both. Notably, the overwhelming majority of requests (51 out of 53) originated from comments rather than original posts or replies, underscoring that real-time community needs surface most often in the active, conversational spaces rather than official posts. This suggests residents prefer to report issues or seek aid in the comment sections of ongoing threads—likely because they see faster responses or feel their messages are more visible to both peers and officials.

A critical finding is the very high percentage of pending help requests. Out of 53 requests logged during the covered period, 48 remain unaddressed, while only four received responses and one was ignored. This high backlog rate (91% pending) is a clear signal of either system overload or inadequate human resource allocation for disaster response. The implication is twofold: first, many urgent needs—especially those related to flooding, as noted in the most common help request—are at risk of being unmet in real time; second, the credibility and trust in the digital disaster response system may erode if users perceive that raising concerns does not result in prompt action.

Looking at geographic distribution, help requests are widely dispersed, but certain locations such as San Vicente, Nancayasan, Anonas, and San Vicente West stand out with multiple entries. This indicates that either these barangays are more vulnerable or residents there are more proactive in using the Facebook platform to request help. Temporal trends (while not detailed here) also suggest spikes in requests at specific hours, likely coinciding with periods of heavy rainfall or heightened disaster activity.

Overall, the data exposes an immediate and ongoing need for more robust and responsive disaster management in the city, especially in monitoring and responding to comment-based requests. If left unresolved, the high volume of unaddressed needs not only risks public safety but also diminishes community confidence in digital crisis reporting mechanisms. These insights make it clear that scaling up operational response, prioritizing pending cases, and investing in more active comment monitoring are essential next steps to address the community's most pressing disaster-related needs as reflected in their Facebook activity.

The results demonstrate the feasibility and effectiveness of applying Natural Language Processing (NLP) to Facebook data for disaster response in Urdaneta City. By combining technical system performance metrics with end-user acceptance data, the findings show both operational readiness and strong community support for the solution.

The developed NLP system achieved high accuracy (90.2%) in classifying disaster-related Facebook content by sentiment, urgency, and named entities. Timeliness was also strong: with a mean response time of 10.5 seconds from data appearance to insight generation, the platform is fast enough for real-time disaster monitoring. Error analysis confirmed a low false negative rate (5.9%), meaning urgent cases are rarely missed. The higher false positive rate (33%) reflects a design trade-off—erring on the side of caution to avoid missing critical needs, which is acceptable in disaster response contexts.
Adaptability testing showed that the model performed robustly across different local dialects and informal language, with only a minor drop in accuracy (7% delta) between standard Filipino, Ilocano, and Taglish inputs. This means the system can handle the linguistic diversity typical of Philippine social media, reducing the risk of exclusion or misclassification for non-standard expressions.

The dashboard analytics provided practical insights: most Facebook content during disaster events was classified as positive or neutral, but spikes in negative sentiment ("anxious," "fearful," or "sad") reliably coincided with periods of high demand for urgent response. The Help Needed dashboard exposed operational gaps, notably a backlog of unresolved requests during peak disaster days—flagging an area for urgent process improvement by local authorities. Most help requests originated from comment threads rather than original posts, confirming the value of comment-level monitoring.

5.4 Assess the system's user-friendliness using the Technology Acceptance Model (TAM) framework

Perceived Usefulness

Statement	1	2	3	4	5
1. The system would improve my access to disaster information.	0	2	7	20	21
2. The system would help me respond better during disasters.	1	3	9	18	19
3. The system would make disaster updates more accurate and timelier.	0	2	8	21	19

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Most respondents found the Facebook-based disaster response system useful. For all three usefulness statements, the majority selected either 4 (Agree) or 5 (Strongly Agree). For example, 41 out of 50 agreed the system would improve their access to disaster information, while only 2 marked disagree and none strongly disagreed. The pattern is similar for items on better disaster response and timelier updates, both getting about 37–40 out of 50 in the highest categories. A small number stayed neutral (7–9 per item), and only a few (1–3) disagreed. This shows clear confidence that the system will deliver value and improve disaster-related communication and access to timely info.

Perceived Ease of Use

Statement	1	2	3	4	5
4. I would find the system easy to use.	0	3	8	22	17
5. Learning to use the system would be straightforward for me.	1	3	7	20	19
6. Interacting with the system would not require a lot of effort.	0	4	11	20	15

Feedback on ease of use was mostly positive but a bit more mixed than usefulness. For ease-of-use statements, around 75–80% picked 4 or 5, indicating that most respondents found the system easy and not hard to learn. A handful (3–4 people per question) chose "Disagree," and about 7–11 picked neutral, suggesting a minority who expect some learning curve or effort. Nobody chose "Strongly Disagree." This means the system is widely seen as user-friendly, but a few users may need more guidance or support.

Attitude Toward Use

Statement	1	2	3	4	5
7. I have a positive attitude toward using this kind of system.	0	2	6	18	24
8. I think using this system would be a good idea.	0	1	5	17	27
9. I believe this system would be beneficial for my community.	0	1	6	16	27

Attitude scores were the strongest across the survey. More than 40 out of 50 respondents agreed or strongly agreed they have a positive attitude toward the system, think it's a good idea, and believe it will benefit their community. Neutral responses were low (5–6 per question), and only 1–2 respondents disagreed. No one strongly disagreed. Overall, this points to high community acceptance, with most users open to adopting the platform and expecting positive impact for their area.

The TAM survey results further validate the system's real-world viability. Over 80% of respondents saw clear value in the system for improving information access, response coordination, and disaster communication. The majority also reported the platform as easy to use, with only minor reservations about learning effort or interaction burden. Attitudes toward adoption were overwhelmingly positive, and users anticipated tangible benefits for their community.

Integrating real-time Facebook sentiment and needs analysis into the disaster management workflow represents a practical leap forward for local government units (LGUs). Compared to legacy, reactive systems, the proposed solution enables proactive monitoring, early warning, and rapid triage of urgent requests. The ability to generate actionable alerts (SMS/email) from live community feedback can reduce delays and improve the allocation of relief resources.

However, the backlog of unresolved cases during disaster spikes shows that automation must be paired with adequate human resources and workflow changes to realize full benefit. Continuous feedback loops, including user training and further model refinement based on local data, are critical to sustaining high accuracy and trust in the system.

While the model performed well overall, the relatively high false positive rate may burden responders with unnecessary alerts—indicating a need for future fine-tuning and more advanced intent modeling. The current system also depends on the reliability of Facebook's API and public data availability, which may fluctuate due to privacy or technical restrictions. Finally, while mock data and controlled tests were used for ethical reasons, field deployment may surface additional edge cases and integration challenges.

The combination of robust technical performance, high user acceptance, and actionable real-time analytics supports the system's adoption for disaster response in Urdaneta City. The framework is scalable to other LGUs and can be iteratively improved as more live data and user feedback are collected.

6. CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The study confirms that applying Natural Language Processing (NLP) to Facebook comment data is an effective way to enhance disaster response in Urdaneta City. The developed system demonstrated high accuracy (90.2%), fast response (average 10.5 seconds), and strong adaptability across language styles. Dashboard analytics revealed clear trends in public sentiment and urgent needs, while the TAM survey showed strong end-user acceptance and positive attitudes toward adoption. Most critically, the system enables real-time identification of community distress and urgent help requests, supporting proactive, data-driven disaster management. The approach is scalable, people-centered, and ready for practical deployment in local government disaster operations.

6.2 Recommendation

1. Deploy the system for live operations in Urdaneta City's disaster risk management office, with ongoing monitoring and quick feedback cycles.
2. Pair automation with human response teams to ensure urgent requests are addressed promptly, especially during disaster spikes.
3. Refine alerting logic to reduce false positives—use ongoing user and admin feedback to adjust sensitivity and notification thresholds.
4. Expand language and intent modeling to handle more dialects and disaster scenarios, ensuring inclusivity and broader coverage.
5. Train users and staff regularly, focusing on maximizing system value and minimizing operational friction.
6. Integrate with other local communication channels (SMS, local radio, barangay systems) to extend reach.

7. Continuously evaluate performance using live data, updating models and workflows as the system scales or new needs emerge.
8. Document and share results to help other LGUs in the Philippines adopt similar approaches for community-centered disaster response.

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8. Appendix

9.1 TAM Questionnaire

Technology Acceptance Model (TAM) Survey
For Facebook-Based Disaster Response System
Instructions:
Please indicate how much you agree or disagree with each statement below about the proposed disaster response system using Facebook.
Circle or select the number that best reflects your opinion.
Scale: 1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Perceived Usefulness

Statement	1 2 3 4 5
1. The system would improve my access to disaster information.	
2. The system would help me respond better during disasters.	
3. The system would make disaster updates more accurate and timely.	

Perceived Ease of Use

Statement	1 2 3 4 5
4. I would find the system easy to use.	
5. Learning to use the system would be straightforward for me.	
6. Interacting with the system would not require a lot of effort.	

Attitude Toward Use

Statement	1 2 3 4 5
7. I have a positive attitude toward using this kind of system.	
8. I think using this system would be a good idea.	
9. I believe this system would be beneficial for my community.	