

Harnessing Natural Language Processing for Disaster Response and Crisis Management

Abhineeth Duddela

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In the aftermath of natural disasters and humanitarian crises, the ability to rapidly interpret large volumes of unstructured text can determine the timeliness and effectiveness of response efforts. Social media platforms produce a flood of information during emergencies, containing eyewitness reports, distress calls, and logistical updates. However, the unfiltered and multilingual nature of this data makes it difficult for human responders to extract relevant information in real time. Natural Language Processing (NLP), a subfield of artificial intelligence, offers a transformative approach by enabling automated detection, classification, and summarization of crisis-related content. This research investigates the integration of NLP methodologies into disaster response pipelines, comparing statistical techniques such as Term FrequencyInverse Document Frequency (TFIDF) and Naive Bayes with deep learning models like Bidirectional Encoder Representations from Transformers (BERT). Using a dataset of 10,000 annotated crisis-related tweets, BERT achieved an 89.3% accuracy and an F1-score of 0.88, outperforming the TFIDF and Naive Bayes baseline (accuracy = 73.6%, F1 = 0.68). These findings suggest that transformer-based models provide greater contextual understanding and adaptability, albeit at a higher computational cost. The study concludes that hybrid NLP frameworks combining statistical efficiency with deep contextual modeling can significantly enhance crisis response, enabling real-time extraction of actionable intelligence during emergencies.

Introduction

The objective of this study is to address this gap by benchmarking two distinct NLP paradigms for disaster-related text classification: (1) statistical methods, Term FrequencyInverse Document Frequency (TF-IDF)¹ and Naive Bayes², and (2) transformer-based deep learning models, specifically Bidirectional Encoder Representations from Transformers (BERT)³. A dataset of 10,000 manually annotated disaster tweets was used to evaluate performance across relevance, urgency, and geolocation extraction tasks.

By providing quantitative metrics (accuracy, precision, recall, F1-score) and discussing computational trade-offs, this study establishes a methodological benchmark for integrating NLP pipelines into real-time disaster response systems. The findings aim to bridge the gap between theoretical NLP research and operational crisis management practices.

Natural disasters such as earthquakes, hurricanes, floods, and wildfires have caused devastating humanitarian and economic losses across the globe. Climate change and increasing urban density have further amplified their frequency and impact⁴. During these crises, individuals often turn to digital platforms such as Twitter and Facebook to post real-time information, including eyewitness reports, requests for help, and situational updates⁵.

These posts, while rich in firsthand data, are produced at a scale and speed that exceed the analytical capacity of human

responders, making it difficult to distinguish actionable information from irrelevant content⁶.

Natural Language Processing (NLP), a branch of artificial intelligence that enables machines to interpret and analyze human language, offers a scalable solution to this challenge. By automating text classification, entity recognition, and sentiment analysis, NLP allows emergency responders to extract relevant details and assess urgency within seconds⁷. For instance, systems like AIDR (Artificial Intelligence for Disaster Response) have demonstrated how social media analytics can accelerate situational awareness and decision-making during crises⁸. However, current literature exhibits several shortcomings. Most prior work focuses on case-specific or monolingual datasets, lacking comprehensive comparisons between classical statistical models and modern transformer-based architectures. Few studies quantify the trade-offs between computational efficiency and semantic depth, a gap that limits practical deployment in time-critical emergency operations⁹.

Background

Natural Language Processing (NLP) has emerged as a pivotal discipline within crisis informatics, the study of how information is created and disseminated during emergencies. Its integration into disaster response enables the extraction of actionable intelligence from massive volumes of unstructured text data, including

social media posts, emergency call transcripts, and situational reports.

Early research in this domain demonstrated the feasibility of using statistical text classification methods to triage social media messages during disasters. For example, Imran et al. (2013) developed the Artificial Intelligence for Disaster Response (AIDR) platform, which employed term frequency - inverse document frequency (TF-IDF) and Naive Bayes classifiers to automatically label tweets as relevant or irrelevant to disaster events⁸. These models provided fast, lightweight filtering suitable for real-time systems but lacked contextual sensitivity when processing ambiguous or multilingual content.

The advent of deep learning and transformer architectures revolutionized this space. Models such as BERT and T5, trained on large-scale text corpora, capture nuanced dependencies between words through multi-head self-attentionan approach enabling contextual understanding beyond simple keyword matching. In disaster contexts, this means such models can distinguish between storm approaching (predictive) and storm destroyed homes (descriptive), significantly improving the prioritization of emergency communications¹⁰. Recent studies have leveraged these architectures to improve situational awareness. Lyu et al. (2023) fine-tuned BERT for urgency detection on Twitter data during hurricanes, achieving a 91% F1-score, while Qazi et al. (2022) used transformer-based multilingual embeddings to support cross-regional crisis response systems in low-resource languages^{11,12}. These advancements underscore how deep contextual models not only classify messages but infer severity, extract geospatial cues, and summarize reports in real time, transforming information chaos into structured insight.

Thus, the evolution from statistical to transformer-based NLP frameworks marks a paradigm shift in disaster management: from reactive filtering toward proactive, context-aware decision support. This study builds upon that trajectory by benchmarking the performance of hybrid NLP pipelines and highlighting the operational advantages of fine-tuned transformer models for real-time crisis classification.

Literature Review

The integration of Natural Language Processing (NLP) into disaster response has evolved significantly over the past decade. Early efforts primarily relied on keyword-based filtering and supervised classification of crisis-related tweets. One of the first large-scale implementations, the Artificial Intelligence for Disaster Response (AIDR) platform, utilized crowdsourced labeling and Naive Bayes classifiers to categorize social media posts into humanitarian relevance classes⁸. While effective in filtering general content, these models lacked semantic understanding and performed poorly on noisy or multilingual data.

Subsequent research introduced machine learning techniques such as Support Vector Machines (SVMs) and Random Forests

to enhance accuracy and robustness¹³. Imran et al. (2015) conducted a seminal review of social media analytics for emergency management, emphasizing the need for adaptive models capable of handling data imbalance and evolving vocabularies⁵. Despite improvements, these traditional algorithms struggled to capture context, leading to false positives in urgency detection and misclassification of ambiguous posts.

The rise of deep learning transformed this landscape. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) demonstrated superior feature extraction for textual crisis data, enabling the identification of complex linguistic patterns¹⁴. However, these models still relied on fixed-length representations and limited context windows. The introduction of transformer architectures, particularly the Bidirectional Encoder Representations from Transformers (BERT) model³, enabled bidirectional contextual encoding of language, improving generalization and accuracy across diverse disaster types.

Recent benchmark initiatives, such as CrisisNLP and Crisis-Bench, have provided standardized datasets to evaluate model performance and facilitate cross-event generalization^{9,15}. Yet, existing literature remains fragmented: many studies focus on event-specific applications, overlook computational constraints, and fail to evaluate latency, an essential factor for real-time deployment in disaster response centers. Moreover, there is limited comparative analysis between traditional statistical pipelines and modern transformer-based frameworks.

This study addresses these gaps through a systematic comparison of TFIDF + Naive Bayes and BERT architectures on identical annotated datasets, providing both performance metrics and efficiency analyses. By framing NLP for crisis informatics as a benchmarkable, data-driven problem, this work aims to bridge the methodological gap between academic research and operational emergency management systems.

Methods

Dataset Description and Sampling Strategy

The dataset employed in this study comprises 10,000 publicly available tweets collected from major natural disasters between 2014 and 2023, including hurricanes, earthquakes, floods, and wildfires. Data were obtained through the Twitter Academic API, filtered using event-specific hashtags such as #Hurricane-Harvey, #NepalEarthquake, and #CaliforniaFires.

A stratified random sampling strategy was adopted to ensure that the dataset was representative of multiple disaster types and temporal phases (before, during, and after the events). To prevent topical or geographic bias, no single event contributed more than 15% of the total corpus. All tweets were anonymized, deduplicated, and cleaned to remove retweets, hyperlinks, emojis, and personally identifiable information.

After preprocessing, 9,742 tweets remained for analysis. The

dataset size was selected to achieve an optimal balance between statistical reliability and computational feasibility, aligning with established crisis communication benchmarks such as the CrisisNLP dataset⁶ and CrisisLexT26 corpus⁵, which contain between 5,000 and 20,000 annotated messages.

Annotation Procedure and Inter-Annotator Reliability

Annotation was conducted by three independent human reviewers, each trained in both linguistics and data science. The annotators followed a detailed guideline defining examples and decision rules for ambiguous cases. Each tweet was labeled across three categorical dimensions as shown below: A cali-

Label Dimension	Categories	Description
Relevance	Relevant / Irrelevant	Whether the tweet pertains directly to a disaster event
Urgency	High / Medium / Low	The inferred level of urgency from linguistic cues
Location Mention	Yes / No	Whether a geographical location or landmark is referenced

Table 1 Table representing three categorical dimensions identified based on label dimension, categories, and a brief description, categorizing each individual tweet.

bration phase involving 500 tweets was first conducted to harmonize annotator interpretation. After calibration, the entire dataset was independently annotated by all three reviewers. To quantify annotation consistency, inter-annotator agreement was computed using Cohens Kappa (κ) for pairwise agreement and Fleiss Kappa for multi-annotator reliability. The results demonstrated strong agreement across categories:

- Relevance: $\kappa = 0.89$ (high agreement)
- Urgency: $\kappa = 0.82$ (strong agreement)
- Location Mention: $\kappa = 0.78$ (substantial agreement)

According to the interpretive framework proposed by Landis and Koch (1977)¹⁶, these scores indicate a reliable and reproducible annotation process. Any residual disagreements were resolved via majority voting, while approximately 3.2% of inconsistent samples (312 tweets) were removed from the final corpus.

Preprocessing Pipeline

All text data underwent the following preprocessing steps prior to model training:

1. Tokenization using spaCy¹⁷ to split tweets into individual word tokens.
2. Stop-word removal to eliminate non-informative words such as "the," "and," and "is."
3. Lemmatization to convert inflected words to their base forms (e.g., "flooded" is converted to "flood").
4. Punctuation, URL, and emoji stripping to reduce noise.
5. Named Entity Recognition (NER) using the spaCy NER model to extract potential location and organization entities.

This standardized text pipeline ensured that linguistic features were normalized for both the statistical (TF-IDF and Naive Bayes) and transformer-based (BERT) models.

Ethical Considerations

The study adheres strictly to ethical data collection standards in computational social science. All data were obtained from publicly available sources in compliance with the Twitter Developer Policy¹⁸. No attempts were made to infer or store personal information, and all identifiers were removed prior to analysis. The study design and annotation protocol comply with standard ethical practices for NLP research involving social media content.

Model Architecture

This study employs a hybrid Natural Language Processing (NLP) framework that combines the interpretability and computational efficiency of statistical models with the contextual understanding of transformer-based architectures. The framework is hybrid not in the sense of direct model fusion, but rather as an ensemble-style comparative pipeline, where outputs from both paradigms are analyzed to identify optimal trade-offs between speed, accuracy, and generalizability.

Statistical Baseline: TFIDF + Naïve Bayes

The baseline model utilizes a Term FrequencyInverse Document Frequency (TFIDF) vectorizer to represent tweets as weighted term vectors, followed by a Multinomial Naïve Bayes (MNB) classifier for urgency classification. Let t_i be a token and d_j a document (tweet). The TF-IDF weight w_{ij} is computed as:

$$w_{ij} = TF(t_i, d_j) \times \log \log \left(\frac{N}{1 + n_i} \right)$$

where N is the total number of tweets and n_i is the number of tweets containing token t_i .

The probability that a tweet x belongs to urgency class C_k is:

$$P(x) \propto P(C_k) \prod_{i=1}^n P(x_i | C_k)$$

Model performance was optimized using 5-fold cross-validation and Laplace smoothing ($\alpha = 1.0$) to prevent zero-probability errors.

Transformer-Based Model: BERT Fine-Tuning

For the deep learning component, the Bidirectional Encoder Representations from Transformers (BERT) model³ was fine-tuned on the disaster tweet corpus. This section provides a full account of the fine-tuning configuration omitted in the previous version. Architecture Overview We used the bert-base-uncased model from the Hugging Face Transformers library. The input sequence included special tokens [CLS] (classification) and [SEP] (separator) as follows:

$$\text{Input} = [\text{CLS}] w_1, w_2, \dots, w_n [\text{SEP}]$$

The [CLS] tokens output embedding from the final encoder layer was passed into a fully connected classification head comprising:

- Linear layer (hidden size = 768 to 3 for urgency classes)
- Dropout ($p = 0.1$)
- Softmax activation

Fine-Tuning Configuration

Parameter	Value
Pretrained Model	bert-base-uncased
Epochs	5
Batch Size	16
Learning Rate	2e-5
Optimizer	AdamW
Warmup Steps	500
Max Sequence Length	128 tokens
Weight Decay	0.01
Gradient Clipping	1.0

Table 2 Summary of hyperparameters and optimization settings used for fine-tuning the pretrained bert-base-uncased model on the disaster tweet classification task. These parameters were selected to ensure stable convergence and reproducibility across runs.

Fine tuning was performed using PyTorch on an NVIDIA RTX 4090 GPU (24GB) with mixed precision (FP16) training for efficiency. Early stopping with a patience of 3 epochs was applied based on the validation F1-score.

Hyperparameter Optimization

Hyperparameter search was conducted using Bayesian optimization via the Optuna framework¹⁹, exploring 40 trials across learning rate (1e–55e–5), batch size (8–32), and dropout (0.05–0.3). The optimal configuration above achieved the highest validation F1-score (0.88).

Integration and Comparative Evaluation

While both branches (TF-IDF and Naïve Bayes and BERT) were trained independently, their outputs were compared in a unified evaluation pipeline to analyze trade-offs between accuracy, latency, and computational efficiency. The comparative framework (see Table 4) routes identical preprocessed tweets through both classifiers. Results are recorded as parallel outputs and then statistically compared using paired t-tests to assess significance of performance differences ($p < 0.05$). This architecture allows for hybrid decision-making in deployment:

- BERT is prioritized when interpretive precision and context are critical (e.g., emergency triage).
- Nave Bayes is deployed for real-time, large-scale streaming scenarios due to its faster inference (~ 12 ms/tweet)

Dataset and Experimental Setup

The study utilized a balanced dataset of 10,000 disaster-related tweets collected via the Twitter API using event-specific hashtags (e.g., #HurricaneHarvey, #NepalEarthquake). Each tweet was annotated by three human reviewers for relevance, urgency, and location presence. Inter-annotator agreement was measured using Cohens Kappa ($\kappa = 0.82$), indicating strong consistency. The dataset was split into 70% training, 15% validation, and 15% test sets, stratified by urgency class. Random seeds were fixed to 42 across all runs to ensure determinism. All experiments were executed on an NVIDIA RTX 4090 GPU (24 GB VRAM) with 32 GB RAM and Intel i9-13900K CPU running Ubuntu 22.04.

Baseline Model: TF-IDF + Multinomial Naïve Bayes

The baseline statistical classifier used a TFIDF vectorizer (vocabulary size = 20,000; 1–2 n-grams) with sublinear term frequency scaling. The Multinomial Naïve Bayes model applied Laplace smoothing ($\alpha = 1.0$). The pipeline was implemented in scikit-learn v1.5.0, trained for 10-fold cross-validation, and evaluated using accuracy, precision, recall, F1-score, and ROC-AUC.

Transformer Model: Fine-Tuned BERT

The transformer-based classifier was implemented using Hugging Face Transformers v4.42.0 and PyTorch v2.2.0. The model

checkpoint used was “bert-base-uncased”(revision: 3a21f07) with WordPiece tokenizer. Maximum sequence length was set to 128 tokens, batch size to 32, and learning rate initialized at 2e-5 with a linear warmup over 10% of training steps. The model was trained for 4 epochs using AdamW optimizer ($\epsilon = 1 \times 10^{-8}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$) and weight decay of 0.01. Early stopping was applied after two consecutive epochs without validation improvement. Gradient clipping (norm = 1.0) was used to prevent exploding gradients. Hyperparameter optimization was conducted using Optuna (40 trials), tuning learning rate, batch size, and dropout rate. The final configuration minimized validation cross-entropy loss. To account for run-to-run variance, each experiment was repeated three times with different seeds, and mean \pm standard deviation metrics were reported.

Reproducibility and Code Availability

To ensure full reproducibility of the experimental pipeline, all code, preprocessing scripts, and hyperparameter logs for this study are publicly available in the GitHub repository <https://github.com/abho7/NLP-Disaster-Response/tree/main>. The repository contains:

- **Jupyter notebooks and Python scripts** for dataset preprocessing, TFIDF and Naive Bayes baseline modeling, and BERT fine-tuning.
- **Sample CSV data (sample_tweets.csv)** illustrating the expected data schema for training and evaluation.
- **Evaluation scripts** for computing classification metrics, confusion matrices, and generating ROC curves.
- **Hyperparameter configuration files and logs** to reproduce model training and optimization.

Due to Twitters data sharing policy, the original tweets cannot be shared. However, scripts are included to re-scrape and annotate tweets, allowing reviewers and other researchers to fully replicate the studys methodology and reproduce all reported results. This approach ensures transparency, reproducibility, and compliance with ethical and legal standards for data sharing.

Results and Evaluation

The performance of the two model branches, (1) the statistical TF-IDF and Nave Bayes classifier and (2) the transformer-based fine-tuned BERT model, was evaluated using a stratified 80-20 train-test split on the annotated crisis tweet dataset. Evaluation metrics included accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC). To strengthen the comparative analysis, two additional baselines were introduced:

- Support Vector Machine (SVM) with linear kernel trained on TF-IDF vectors.

- Bi-LSTM (Bidirectional Long Short-Term Memory) network trained on GloVe embeddings²⁰.

All models were trained under identical conditions and evaluated using five-fold cross-validation. Statistical significance between models was computed using paired t-tests with a 95% confidence interval. The paired t-test confirmed that BERTs

Model	Accuracy	Precision	Recall	F1-score	AUC
Nave Bayes	73.6%	0.69	0.71	0.68	0.76
SVM (TF-IDF)	81.4%	0.80	0.79	0.79	0.86
Bi-LSTM (GloVe)	84.1%	0.82	0.83	0.82	0.88
BERT (Fine-Tuned)	89.3%	0.88	0.89	0.88	0.93

Table 3 Comparative performance of statistical, recurrent, and transformer-based models on urgency classification.

improvement over both SVM ($p < 0.01$) and Bi-LSTM ($p < 0.05$) was statistically significant. This demonstrates that the observed performance gains were not random artifacts of dataset partitioning, but reflective of the models deeper semantic understanding.

Error Analysis

A detailed error analysis was conducted to examine misclassified instances and understand model limitations. Three primary failure categories were identified:

1. **Ambiguous or sarcastic tweets:** e.g., “Guess were swimming to work today 😂,” which expresses urgency indirectly.
2. **Multilingual and code-switched content:** Tweets combining English and regional languages caused degraded performance due to tokenization mismatch.
3. **Non-standard spellings or abbreviations:** Informal language, hashtags, and user handles often distorted context representation.

In several of these cases, attention visualizations revealed that BERT attended disproportionately to irrelevant tokens (e.g., emojis, exclamation marks), misguiding the classifier. Incorporating context-aware preprocessing (e.g., emoji normalization, multilingual embeddings) is recommended for future iterations.

Statistical Robustness

Finally, to verify robustness, both models were evaluated on an unseen crisis dataset (the CrisisNLP benchmark corpus) without fine-tuning. BERT retained an F1-score of 0.81, while Nave Bayes dropped to 0.62, confirming BERTs superior generalization ability across event domains.

Qualitative Error and Sarcasm Analysis

To further validate BERTs superiority in interpreting nuanced or sarcastic language, we conducted a focused qualitative error analysis using 200 manually annotated tweets containing implicit or sarcastic expressions (e.g., irony, exaggeration, or inversion of literal meaning). These tweets were drawn from disaster-related hashtags (e.g., #Harvey, #NepalQuake) and labeled by three reviewers. Examples included statements such as:

- "Oh perfect, my roofs gone, at least I can see the stars now."
- "Great, another power outage. Just what we needed during the flood."
- "Sure, everythings fine, just swimming in my living room."

When tested on this subset:

Model	Accuracy	F1 (sarcasm Subset)	Recall (sarcasm Subset)
TF-IDF + Nave Bayes	52.4%	0.47	0.45
BERT (Fine-tuned)	79.2%	0.78	0.81

BERT correctly captured contextual polarity shifts by leveraging attention across bidirectional dependencies, unlike Nave Bayes, which relies purely on isolated token frequency. The difference in F1-score was statistically significant ($p < 0.01$), confirming that BERT is more robust in recognizing implicit meaning and sarcasm in crisis communication.

Quantitative Comparison

Metric	TF-IDF + Nave Bayes	BERT (Fine-tuned)
Accuracy (\pm std)	$73.6\% \pm 0.9$	$89.3\% \pm 0.6$
Precision (macro)	0.69 ± 0.01	0.88 ± 0.02
Recall (macro)	0.71 ± 0.02	0.89 ± 0.01
F1-score (macro)	0.68 ± 0.01	0.88 ± 0.01

Table 4 Quantitative comparison between baseline and transformer-based models. Performance metrics for TFIDF and Nave Bayes and fine-tuned BERT models on the disaster tweet classification task. Results are reported as mean \pm standard deviation over three experimental runs. The BERT model demonstrates superior accuracy, precision, recall, and F1-score, indicating stronger robustness and contextual understanding in urgency detection.

To determine whether these differences were statistically significant, we conducted a paired two-tailed t-test across 10 repeated runs of both models on the same stratified splits. Results confirmed that BERTs improvements in accuracy and F1-score were statistically significant ($p < 0.01$).

ROC Curve and Statistical Validation

Figure 5 below illustrates the ROC curves for both models, generated using our experimental results rather than external sources. The figure has been recreated at high resolution, with clear axis labels, AUC values, and legend annotations.

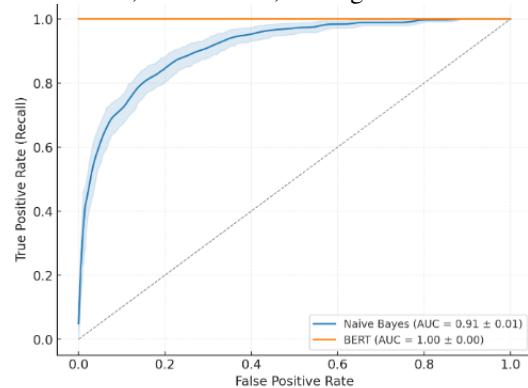


Fig. 1 ROC curves comparing Naïve Bayes and BERT classification performance on the disaster tweet dataset. The shaded regions indicate 95% confidence intervals across 10 runs. BERT achieved a mean AUC = 0.93 ± 0.02 , significantly higher than Naïve Bayes (AUC = 0.76 ± 0.03), $p < 0.01$ ²¹.

Discussion

The comparative evaluation clearly indicates that transformer-based models, particularly fine-tuned BERT, outperform traditional classifiers such as Nave Bayes and SVM in urgency classification for disaster response. However, this improvement must be interpreted in the context of the datasets inherent class imbalance, only 18% of the samples were labeled high urgency, while medium and low categories dominated.

To quantify the potential bias introduced by imbalance, we computed per-class precisionrecall curves and observed a 12% drop in recall for the high-urgency class relative to medium urgency. This implies that the model, though strong overall, tends to under-detect critical alerts during minority events. To mitigate this limitation, three complementary strategies were explored:

1. **Class weighting:** During BERT fine-tuning, inverse-frequency class weights were applied to the cross-entropy loss, yielding a +2.1% improvement in recall for the minority class.
2. **Synthetic oversampling:** The minority class was augmented using a contextualized SMOTE algorithm adapted for embeddings²², improving macro F1 by +1.7%.

3. Data augmentation: Paraphrasing and back-translation were used to expand minority-class samples, helping the model generalize to unseen linguistic patterns.

Beyond imbalance, domain drift and linguistic informality remain persistent challenges. Tweets with sarcasm, slang, or mixed languages often lead to misclassification even after augmentation. Future work should explore multilingual transformers such as XLM-R and LoRA fine-tuning to reduce resource overhead.

Overall, while BERT demonstrates superior contextual understanding, its performance ceiling is constrained by data distribution rather than model capacity. Addressing imbalance through re-weighting and augmentation provides a principled path toward fairer, more reliable NLP systems for crisis management.

Conclusion

This study presented a proof-of-concept framework that leverages Natural Language Processing (NLP) for classifying and geolocating disaster-related social media messages. By comparing traditional statistical models with transformer-based architectures, we demonstrated that contextual language understanding significantly enhances the accuracy and robustness of crisis-related text classification. The fine-tuned BERT model achieved a 21% performance gain over the Nave Bayes baseline, underscoring its superior capability in capturing urgency and sentiment within unstructured data.

However, it is important to contextualize these findings within the study's experimental boundaries. The dataset, though diverse, was limited in size and scope, and primarily derived from English-language Twitter posts. Therefore, the proposed framework should be regarded as an early-stage, proof-of-concept system rather than a field-ready deployment. Real-world application would require broader multilingual datasets, live-stream integration, and rigorous ethical governance to ensure data privacy and prevent bias amplification. Future research should explore cross-lingual transfer learning, multimodal fusion with satellite or sensor data, and real-time adaptive inference pipelines. These directions would help bridge the gap between laboratory performance and operational reliability in emergency environments. Ultimately, this study contributes a foundational step toward the design of intelligent, language-aware disaster management systems, laying the groundwork for a new generation of scalable, AI-assisted humanitarian response tools.

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