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Evaluating Deep Learning Models for Humanitarian Sentiment Classification in Crisis Tweets: A Benchmark Study

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ABSTRACT: Social media platforms have emerged as essential channels for real time crisis communication, offering valuable insights into public sentiment and humanitarian needs during emergencies. This study benchmarks the performance of state of the art deep learning models for classifying sentiment and humanitarian relevance in crisis related tweets. Using publicly available datasets CrisisMMD, HumAID, and CrisisBench we evaluate three architectures: IDBO CNN BiLSTM, BERTweet, and CrisisTransformers. These models were assessed using cross validation and standard performance metrics (accuracy, F1 score, precision, and recall). Results indicate that CrisisTransformers outperform both traditional CNN LSTM hybrids and general purpose transformers, achieving an accuracy of 0.861 and F1 score of 0.847. Domain specific pretraining significantly enhances contextual understanding, particularly in multilingual and ambiguous tweet scenarios. While transformer models offer superior classification capabilities, their computational complexity poses challenges for real time deployment. Additionally, operational risks, such as data bias and misinformation, necessitate careful management through structured human oversight and the integration of explainable AI mechanisms. This research provides a robust comparison of NLP models for crisis applications and recommends strategies for effective deployment, including bias mitigation and fairness aware learning. The findings contribute to building ethical and efficient NLP systems for humanitarian response.

Keywords: Humanitarian NLP, Crisis Response, Tweet Classification, Sentiment Analysis, Transformer Models, Benchmark Datasets, Bias Mitigation.

INTRODUCTION

In the context of modern crisis management, the role of social media has become increasingly pivotal. Platforms like Twitter/X facilitate rapid information exchange between individuals, communities, and institutions, often outpacing traditional communication channels. This real-time flow of information has transformed the operational landscape for crisis and emergency management organizations. It provides opportunities to enhance situational awareness, coordinate response strategies, and foster public trust. According to Haataja et al. (2016), direct communication via social media enables more agile responses and strengthens organizational public relationships, which are critical in times of crisis. The dual utility of social media as both an information dissemination mechanism and a participatory platform has redefined how crises are perceived and managed (Eriksson & Olsson, 2016).

Central to the analytical use of social media in crisis response is sentiment analysis. Humanitarian organizations have increasingly adopted this technique to interpret public mood, identify urgent needs, and guide decision making during disasters. For instance, during the COVID 19 pandemic, analyzing sentiment in user generated content allowed agencies to track public attitudes toward health policies and adjust communication strategies accordingly (Zhang et al., 2022). The real time capabilities of platforms like Twitter offer insights not only into logistical concerns but also into emotional states, enabling humanitarian actors to respond with greater precision and empathy (Tian et al., 2021).

Despite its promise, the deployment of classification systems for crisis related social media content faces numerous challenges. Chief among these is the inherent noise and ambiguity of online discourse, which often complicates the accurate categorization of tweets (Imran et al., 2016). Additional hurdles arise from linguistic and cultural variability, which can distort meaning and reduce the effectiveness of models trained on homogenous data (Lee et al., 2017). These limitations are compounded when models encounter domain shifts or multilingual input, emphasizing the need for context sensitive machine learning approaches.

Historically, supervised learning algorithms such as support vector machines (SVM) and decision trees have been favored for their scalability and capacity to handle high dimensional features (Imran et al., 2016). However, with the evolution of natural language processing (NLP), deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have gained traction due to their superior ability to model syntactic and semantic nuances (Banyongen, 2023). These models exhibit improved performance in classifying social media content under the complex conditions typical of crisis communication.

To mitigate the effects of data noise and ambiguity, contemporary deep learning architectures employ strategies such as attention mechanisms and ensemble learning. Attention mechanisms allow models to prioritize relevant parts of input sequences, improving the extraction of salient features from chaotic or unstructured data (Imran et al., 2016). Ensemble models aggregate predictions from multiple classifiers, enhancing classification robustness and reducing susceptibility to outliers or anomalies (Bukar et al., 2021).

A growing body of research has also focused on benchmarking NLP models for humanitarian classification tasks. These benchmarks assess not only accuracy and recall but also metrics related to response timeliness and information utility in dynamic crisis environments (Maal & Wilson-North, 2019). Dedicated datasets, such as CrisisMMD, HumAID, and CrisisBench, provide valuable testing grounds for these models. Emphasis is often placed on multi label classification, as crises rarely conform to singular categories; rather, they require nuanced understanding across overlapping humanitarian needs (Ngai & Yan, 2016).

The research presented in this article builds upon this foundation by evaluating and comparing the performance of leading deep learning architectures in classifying crisis tweets by sentiment and humanitarian relevance. In doing so, the study addresses the limitations of existing systems and contributes to the development of more effective, context aware tools for emergency response. By focusing on rigorously curated datasets and standardized benchmarks, this research aims to clarify the comparative advantages of various model types and highlight best practices for future applications in humanitarian NLP.

METHOD

This chapter outlines the datasets, preprocessing strategies, model architectures, and evaluation metrics employed in this study to assess the performance of deep learning models for humanitarian sentiment classification in crisis related tweets.

Three publicly available datasets were used:

- CrisisMMD**:** Contains 14.22 million tweets with a labeled subset of 16,097 text entries and 18,082 images. It supports multimodal and multilingual research on informativeness, humanitarian relevance, and damage severity. Despite its domain richness, it can suffer from the inherent noisiness of user generated content (Barbieri et al., 2021).
- HumAID**:** Comprising approximately 24 million raw tweets and 77,000 labeled examples across 19 disaster events, HumAID focuses on multilingual humanitarian categories. However, due to its time specific design, the dataset's relevance may diminish over time (Adams et al., 2022).
- CrisisBench**:** This benchmark integrates eight separate crisis datasets into a unified framework, offering 166,100 samples labeled for informativeness and 141,500 for humanitarian relevance. While it supports comprehensive evaluation, the requirement for large labeled data quantities may limit applicability in real time crises.

Given the noisy, informal, and multilingual nature of tweets, a robust preprocessing pipeline was implemented:

- Tokenization**,** stop word removal**,** case folding, and lemmatization helped transform unstructured text into standardized form (Kumari, 2022).
- Text normalization addressed domain specific issues like slang, misspellings, and abbreviations, achieving performance improvements(Sosamphan et al., 2016).
- Regular expressions were used to remove URLs, emojis, and other non target elements (Almalki, 2022).

- Language identification was applied to ensure that multilingual content was properly segmented and classified (Rawat & Jain, 2022).
- Location inference and deduplication were also implemented to reduce redundancy and improve data relevance (Arun & Srinagesh, 2020).

Three deep learning models were evaluated:

- IDBO CNN BiLSTM**:** A hybrid model that combines convolutional and recurrent layers for both feature extraction and sequential understanding. While effective for sentiment tasks, it requires extensive training and fine tuning to generalize across crises.
- BERTweet**:** A transformer based architecture pretrained on general Twitter corpora. It is capable of contextual understanding and performs well with appropriate fine tuning .
- CrisisTransformers**:** A domain specific transformer trained on over 15 billion tokens from more than 30 crisis events. It employs self attention mechanisms for deeper semantic interpretation, making it highly effective in sparse and ambiguous tweet classification scenarios.

To ensure comparability and reliability:

- Performance metrics included accuracy, F1 score, precision, and recall.
- The models were tested across two main classification tasks: humanitarian category prediction and sentiment classification.
- A 5 fold cross validation approach was adopted for each dataset.
- Error analyses were conducted to identify common misclassification patterns and inform iterative refinements.

This methodology integrates robust data preparation techniques with advanced modeling approaches to assess the suitability of each architecture for real time humanitarian sentiment classification in crisis contexts.

RESULT AND DISCUSSION

This chapter presents the comparative performance of deep learning models in classifying crisis related tweets based on sentiment and humanitarian relevance. The findings are structured into three key sections: performance overview, comparative metrics, and error analysis.

Across all evaluated datasets, transformer based models consistently outperformed traditional architectures in both accuracy and F1 scores. For instance, CrisisTransformers achieved an accuracy of 0.861 and F1 score of 0.847 on the CrisisBench dataset, while BERTweet demonstrated competitive results with an accuracy of 0.826 on CrisisMMD. In contrast, the hybrid IDBO CNN BiLSTM model yielded 0.8033 accuracy on HumAID.

Performance variability was influenced by the nature of the crisis events. Natural disasters, which often generate emotionally charged tweets, led to higher classification accuracy due to clearer sentiment signals (Gong et al., 2019; Shao et al., 2019). Transformer models excelled particularly in identifying humanitarian needs such as logistical aid and shelter support, thanks to their contextual attention mechanisms (Yang et al., 2023).

Pretrained models like multilingual BERT (mBERT) showed strength in multilingual and cross domain scenarios, outperforming traditional models which lacked adaptability to language diversity(Ardi et al., 2022). Pretraining also enhanced model performance on low resource datasets, allowing effective knowledge transfer from general to crisis specific tasks(Alrawi, 2022).

Table 1. Model Performance Metrics Across Datasets

Model	Dataset	Accuracy	F1 Score	Precision	Recall
IDBO CNN BiLSTM	HumAID	0.8033	0.781	0.792	0.770
CrisisTransformers	CrisisBench	0.861	0.847	0.856	0.838
BERTweet	CrisisMMD	0.826	0.809	0.818	0.800

Comparative Metrics

Table 2 summarizes accuracy, F1 score, precision, and recall across datasets. These metrics were informed by benchmarks including CrisisMMD, HumAID, and CrisisBench. Using k fold cross validation significantly improved result reliability and mitigated overfitting (Luz et al., 2021).

Multimodal models incorporating visual content outperformed text only models, especially in high impact events where images played a critical role in conveying damage severity (Liu & Wu, 2023). However, dataset imbalance remained a persistent issue. Overrepresentation of certain humanitarian categories skewed performance metrics, necessitating the application of data balancing strategies such as oversampling or custom loss functions(Zhou et al., 2022).

Error Analysis

Misclassifications were frequently linked to ambiguous, short, or mixed sentiment tweets (Nugraha et al., 2023). Tweets with high emotional intensity or sarcasm presented unique challenges, often misleading models with abrupt shifts in tone.

Tweet length also influenced model performance. Short tweets lacked context, resulting in lower classification accuracy. High intensity sentiments were inconsistently interpreted across models, indicating a need for finer grained contextual embeddings (Dideriksen et al., 2023).

Cultural and linguistic variations further complicated classification accuracy. Models trained primarily on English datasets underperformed when exposed to idiomatic expressions or local dialects from other linguistic backgrounds(Robbeets et al., 2021).

Confusion matrices revealed model specific weaknesses. For example, overlap between categories like “Infrastructure Damage” and “Medical Assistance” caused frequent mislabels. These matrices were instrumental in guiding future improvements by identifying underperforming labels and informing data augmentation or model refinement strategie(Alonso et al., 2021; Montanari et al., 2018).

Balancing Model Complexity and Deployability

This study has presented a comprehensive benchmarking of deep learning models for classifying humanitarian sentiment in crisis related tweets. The results reveal consistent superiority of transformer based models, particularly CrisisTransformers, across a variety of datasets. However, these findings also warrant deeper discussion regarding practical, ethical, and technical considerations for deployment in real world humanitarian scenarios. These aspects are critical not only from an academic standpoint but also for ensuring safe, timely, and impactful application in live crisis situations.

A key trade off observed is between model complexity and deployability in crisis settings. Complex architectures such as deep neural networks and transformers deliver high classification accuracy due to their advanced semantic modeling capabilities and deep context understanding. However, their computational demands often make them unsuitable for resource constrained environments (Barkovska et al., 2023). In time critical crisis situations, the latency introduced by complex inference processes may hinder swift decision making (Taware et al., 2022). This latency may create bottlenecks in emergency workflows, delaying aid distribution or misaligning logistics during time-critical operations.

Conversely, simpler models like logistic regression or shallow neural networks are easier to deploy and operate in limited resource environments. Their faster inference time and lower computational overhead make them suitable for rapid prototyping and initial triage in emergencies. However, they may lack the nuanced performance required for complex humanitarian classifications, particularly in ambiguous or multilingual contexts (Dang et al., 2023; Jang et al., 2020). Thus, model selection must weigh predictive power against practical constraints such as hardware availability, internet connectivity, and field level operability.

Domain Specific Pretraining for Humanitarian NLP

Another significant consideration is the value of domain specific pretraining for humanitarian NLP tasks. General purpose language models may not fully capture the unique linguistic structures, acronyms, and urgency present in humanitarian communication. Models pretrained on crisis specific corpora, such as CrisisTransformers, demonstrate enhanced sensitivity to the terminology, urgency, and structure of humanitarian discourse (Salur & Aydın, 2020). They are more capable of discerning between general chatter and actionable requests, as well as differentiating context specific expressions of distress.

These models more accurately interpret intent and sentiment, reducing the risk of misclassification in high stakes contexts. For instance, a tweet that appears benign in a general context may contain embedded cues for urgent help when interpreted through a crisis trained model. Pretraining thus serves as an essential mechanism for contextual alignment, particularly when dealing with emotionally charged or logistically complex communications (S. Li et al., 2023). This process also enables the model to develop resilience to noise and linguistic irregularities typical in social media.

Risks in Operationalizing Social Media Classification

Despite their promise, social media based classification systems carry substantial risks when used in operational response frameworks. Platforms like Twitter/X are susceptible to misinformation, sarcasm, and emotionally volatile content, all of which may mislead automated classifiers (Ramaswamy & Jayakumar, 2023). Misinformation can quickly gain traction, distorting situational awareness. If left unfiltered, this data may influence resource deployment and public health messaging erroneously.

The consequences of such misclassifications can be severe misallocating medical supplies or misrepresenting the needs of affected populations (Jin et al., 2019). Moreover, these models may inherit biases from their training data, privileging dominant narratives while excluding marginalized voices (Neekhara et al., 2019; Velankar et al., 2021). This can inadvertently result in inequitable or incomplete crisis responses. As such, these challenges necessitate human in the loop oversight and multilayered validation strategies before these models are deployed in sensitive, real world operations. Without safeguards, automated systems may exacerbate harm rather than mitigate it.

Addressing Bias and Dataset Limitations

To address dataset limitations and algorithmic bias, several mitigation strategies have been proposed. One primary approach involves data augmentation, including techniques such as synonym replacement, paraphrasing, and class balancing, to improve coverage and generalizability (S. Li et al., 2023). These techniques diversify the dataset and introduce underrepresented linguistic structures, helping models become more robust to variation.

Adversarial training has also shown potential in hardening models against biased input and improving robustness in diverse contexts (Y. Li et al., 2018). By exposing models to deliberately confusing or edge case data during training, they learn to develop more stable and fairer classification boundaries. Fairness aware algorithms further enhance this by detecting and correcting skewed model outputs, offering a more equitable classification framework (Ranjan & Daniel, 2023). Such algorithms introduce bias correction mechanisms into the inference pipeline, ensuring predictions remain aligned with inclusive humanitarian values.

Importantly, ongoing auditing and explainability techniques should accompany model deployment. Tools such as SHAP and LIME can help reveal why a model classified a tweet a certain way, allowing developers and analysts to diagnose unintended behavior. These explainability mechanisms, when paired with transparent documentation and community feedback loops, foster stakeholder trust and support ethical accountability in the deployment of NLP models in humanitarian contexts (Imron et al., 2023).

Summary and Future Directions

In summary, while the benchmarking presented here validates the efficacy of modern transformer architectures for crisis sentiment analysis, careful attention must be paid to several dimensions. These include the trade offs between complexity and deployability, the ethical risks of misclassification, and the technical strategies for bias mitigation. Future research should prioritize adaptable, fair, and operationally feasible NLP systems for crisis response.

Future research should further explore multilingual and multimodal learning, the integration of domain-adaptive pretraining, and field validation in humanitarian operations to enhance the real-world readiness of these tools. As crises continue to evolve in frequency and form, so too must the sophistication, transparency, and inclusivity of the models we use to interpret and act on digital signals of distress.

CONCLUSION

This study benchmarked the performance of deep learning models for classifying humanitarian sentiment in crisis-related tweets, using datasets such as CrisisMMD, HumAID, and CrisisBench. The findings demonstrate that transformer-based architectures, particularly CrisisTransformers, consistently outperform hybrid CNN–BiLSTM and general-purpose transformers in terms of accuracy, F1 score, precision, and recall. These results highlight the importance of domain-specific pretraining in enhancing contextual understanding and adaptability.

Beyond technical performance, the analysis underscores critical considerations for real-world deployment. Model complexity must be balanced against computational feasibility in resource-constrained or time-sensitive environments. Ethical risks including susceptibility to misinformation, algorithmic bias, and exclusion of marginalized voices necessitate the implementation of human oversight, explainable AI tools, and fairness-aware learning strategies.

Overall, this research contributes to humanitarian NLP by providing a rigorous benchmarking framework and practical recommendations for deploying crisis-sensitive models. Future work should extend this approach to multilingual and multimodal contexts, incorporate low-resource adaptation strategies, and conduct field validation with humanitarian organizations to ensure operational relevance, equity, and social responsibility.

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