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**A Multi-Model Approach for Disaster-Related Tweets: A Comparative Study of Machine Learning and Neural Network Models**Parth Mahajan<sup>1</sup>, Pranshu Raghuwanshi<sup>2</sup>, Hardik Setia<sup>3</sup>, and Princy Randhawa\*<sup>1</sup><sup>1</sup>Department of Mechatronics, Manipal University Jaipur, Jaipur, India 303007<sup>2</sup>Department of Computer Science & Engineering, Manipal University Jaipur, Jaipur, India 303007<sup>3</sup>Department of Information Technology, Manipal University Jaipur, Jaipur, India 303007**Abstract**

This research centres around utilization of Natural Language Processing (NLP) techniques for the analysis of disaster-related tweets. The rising impact of global temperature shifts, leading to irregular weather patterns and increased water levels, has amplified the susceptibility to natural disasters. NLP offers a method for quickly identifying tweets about disasters, extracting crucial information, and identifying the types, locations, intensities, and effects of each type of disaster. This study uses a range of machine learning and neural network models and does a thorough comparison analysis to determine the best effective method for catastrophe recognition. Three well-known techniques, including the Multinomial Naive Bayes Classifier, the Passive Aggressive Classifier, and BERT (Bidirectional Encoder Representations from Transformers) were carefully examined with the ultimate goal of discovering the best strategy for correctly recognising disasters within the context of tweets. Among the three models, BERT achieved the highest performance in analyzing disaster-related tweets with an accuracy of 94.75%.

**Keywords:** Disaster-Tweets; Disaster Management; Machine Learning; Natural Language Processing**1 Introduction**

Global warming and increasing sea levels have increased the frequency of natural disasters, which are characterized by irregular weather patterns and ecological imbalances. Therefore, there is a critical need for the management of these natural disasters [1]. This research focuses on the pivotal role of Natural Language Processing (NLP) in extracting disaster-related information from Twitter. NLP, which empowers computers to comprehend human language, facilitates the extraction of essential details from disaster-related tweets, encompassing disaster categorization, locations, severity, and impacts. Amidst challenges like evolving language and ambiguous expressions in tweets, NLP emerges as a solution for swiftly identifying disasters, issuing early warnings, and enabling rapid responses. The study adopts a variety of NLP techniques, combining machine learning approaches like Multinomial Naïve Bayes and Passive Aggressive Classifiers with neural network models such as BERT. A comprehensive comparative analysis of these models is conducted to identify the optimal performer and evaluate its present and future scalability in real-world applications. Throughout the research, challenges posed by shifting language trends and unclear language in tweets are addressed through iterative model enhancements and a refined grasp of contextual nuances. The research also encompasses understanding public perceptions of disasters and their consequent behavioral shifts, thereby refining communication strategies for emergency response agencies. This study addresses the essential need for improved disaster management approaches, emphasizing the critical role of NLP in lessening the impact of catastrophic occurrences on society. The study's conclusion aims to develop not only catastrophe management tactics, but also the larger landscape of NLP applications.

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## 2 Related Work

During natural disasters, social media plays an important role in spreading awareness, helping to share vital data, request help, and reach out for aid for those affected [2]. As a valuable real-time data source, Twitter offers a feasible solution for analysis. However, capturing the behavior and emotions within natural disaster tweets remains a complex task in sentiment analysis [3]. To address the large volume of real-time data from Twitter, a partially automated AI-based system is proposed. This system would be responsible for extracting vital information related to the disaster and the tentative affected areas [4]. An advanced approach needs to be developed, employing various machine learning tools and data-driven sentiment analysis. Techniques like Naive Bayes and SVMs can be valuable in this context, aiding in real-time sentiment assessment across crucial areas relevant to disaster response and public perception [5]. Passive aggressive online learning is an extension of SVM to the context of online learning for binary classification. PA and APA algorithms outperformed SVM, achieving state-of-the-art results. Both PA and APA are computationally less expensive than SVM and can scale easily to labeling large datasets [6]. Limited lifespan sensors continuously swap out new features for old ones while exchanging data. This makes online algorithms efficient at learning linear classifiers from datasets with fixed or trapezoidal feature spaces [7].

In natural language processing, bag-of-words and word embeddings are widely used for representing textual features in various machine learning and deep learning models, each chosen based on its effectiveness for specific tasks. For example, bag-of-words performs well with SVM and Logistic Regression, while word embeddings often have an advantage in CNNs and LSTMs [8]. In recent times, word embeddings techniques (i.e., transformer-based) have improved the capabilities of disaster detection models by capturing contextual nuances of language. However, research on this model is scant [9]. Presently, many complex problems of image recognition, speech recognition, and natural language processing are best dealt with by neural networks and deep learning [10]. While BERT embeddings have demonstrated successful utilization across a range of Natural Language Processing (NLP) tasks, their specific usefulness in the analysis of disaster-related tweets lacks a comprehensive analysis [11]. BERT utilizes a transformer architecture that consists of two key components: a decoder responsible for generating task predictions and an encoder that processes the input text. The encoder focuses on learning contextual relationships between words or sub-words within the text. Unlike sequential models that read the text in a specific direction, BERT's transformer encoder comprehends the entire sequence of words simultaneously. This bidirectional approach helps BERT to understand the context of a given text by considering the surrounding words from both the right and left sides. In essence, BERT leverages its unique ability to grasp the broader context of text based on its entire context, enhancing its understanding capabilities [12, 13].

Enhancing the accuracy of detection by effectively leveraging keywords poses a significant challenge. One potential approach to address this is by employing pair-wise training to finetune BERT. This involves using pairs of Tweets that share the same keywords but have opposite training labels. By doing so, BERT is compelled to gain a deeper understanding of the contextual distinctions between the two Tweets, thereby improving its performance [14]. Gradient descent is widely recognized as a highly favored algorithm for optimization, especially in the realm of machine learning. Its stochastic variant has gained significant attention in recent times, particularly when optimizing deep neural networks. Within deep neural networks, leveraging the gradient of a single sample or a batch of samples has proven beneficial, as it helps conserve computational resources and navigate away from challenging points known as saddle points.

## 3 Methods

The steps mentioned in Figure 1 were implemented for achieving the results. Multinomial Naïve Bayes (MNB) model was utilized to determine the likelihood of documents belonging to specific classes. By employing Bayes' theorem and assuming feature independence given the class, MNB calculated the occurrence likelihood of each feature within each class and the prior probability of each class. The class with the highest posterior probability was predicted. MNB efficiently processed large-scale datasets with high-dimensional feature spaces, which are typical in text classification tasks, thanks to its simplicity and efficiency. Despite the "naïve" assumption of feature independence not always holding true due to word correlations, MNB frequently demonstrated good practical results, effectively serving as a baseline model for text classification tasks. Passive-Aggressive Classifiers (PAC) algorithm operated by maintaining a weight vector that defined the classification model. When presented with new data, the classifier predicted the class based on the current model parameters. If the prediction was incorrect, the algorithm updated the model using a learning rule that minimized losses and refined the decision boundary. One of the key strengths of Passive-Aggressive classifiers was their ability to accommodate shifting data distributions and concept drift. This adaptability stemmed from their online learning nature, allowing them to integrate new instances while retaining previously acquired knowledge. Their memory efficiency further contributed to their suitability for resource-constrained settings. Nevertheless, Passive-Aggressive classifiers had a sensitivity to noise and outliers, which could result in overfitting. To mitigate this issue, regularization techniques were employed, enhancing the overall effectiveness of these classifiers in the research [15, 16]. The "bert\_en\_uncased\_L-12\_H-768\_A-12" BERT model introduced a new approach to language understanding, considering both left and right context to grasp word meanings more effectively. This allowed the model to grasp word meanings within their context more effectively. The pre-trained BERT model underwent fine-tuning using smaller datasets for disaster-related tweets. This step enabled BERT to adapt its acquired knowledge to various NLP tasks, ultimately leading to improved performance and generalization.

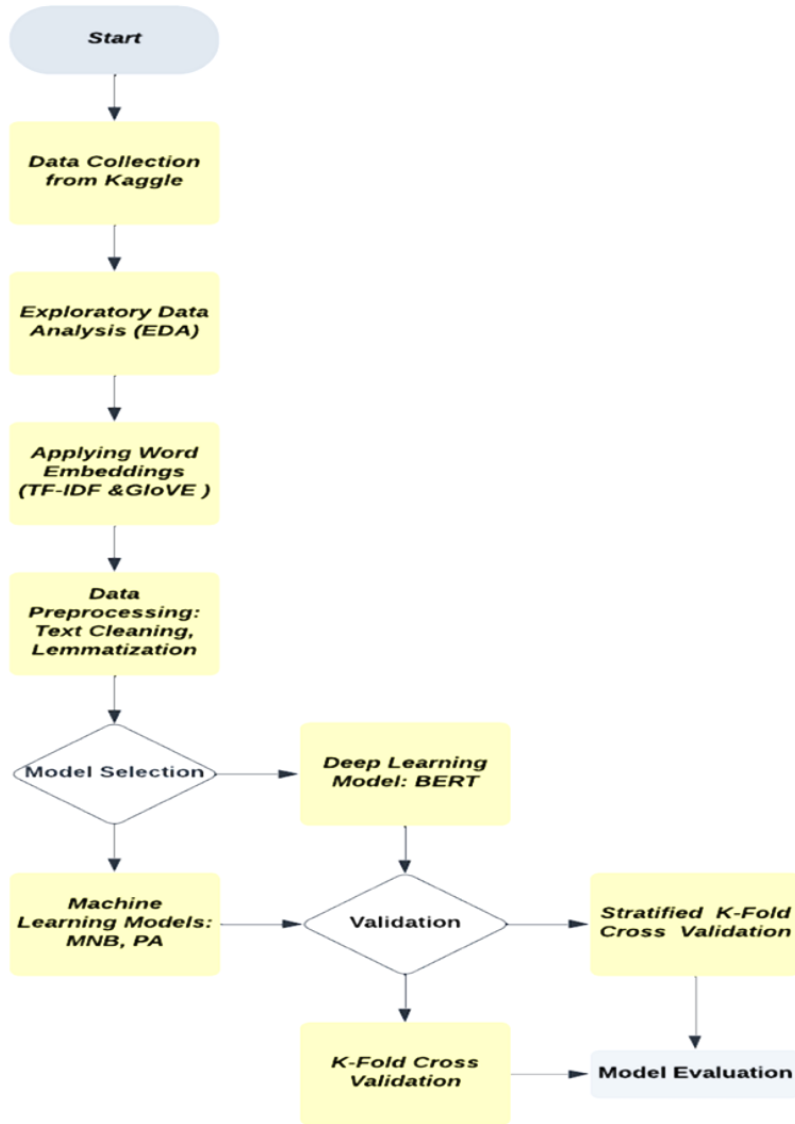


Figure 1: Steps implemented for model training.

Key attributes of the "bert\_en\_uncased\_L-12\_H-768\_A-12" model included its contextual understanding, sentence relationship comprehension, and autonomy in learning features from raw text data, reducing the need for extensive feature engineering [17]. Architecturally, the model featured 12 transformer layers with self-attention mechanisms, capturing dependencies. Its 768-dimensional hidden size represented tokens, while 12 attention heads captured diverse dependencies. The "uncased" vocabulary treated uppercase and lowercase letters alike, enhancing generalization [18]. After pre-training, fine-tuning refined the model's specialization through labeled data [19]. While BERT empowers state-of-the-art performance through transfer learning and contextualized representations, it's important to note that its size comes with limitations. Its extensive training demands significant computational resources, and fine-tuning for specific tasks can be complex. The data for model training was collected from a pre-segregated database off Kaggle.com. It consisted of 7613 unique entries classified as '0' (non-disaster) or '1' (disaster). The dataset features columns such as id (a unique identifier for each tweet), text (the actual content of the tweet), location (the location from which the tweet was sent, which may be blank), keyword (a specific keyword extracted from the tweet, which may also be blank), and target (present only in the training dataset, indicating whether a tweet is about a real disaster or not). The dataset was curated by collecting tweets from Twitter's API based on specific keywords related to disasters, followed by manual labeling to indicate whether the tweets were about real disasters. This dataset is sourced from Kaggle's competition on disaster tweet classification (Kaggle, 2021), provided for educational and research purposes to encourage the development of models capable of identifying tweets related to disasters. In the process of model training, TF-IDF and GloVe embeddings were applied for machine learning models and deep learning models respectively. TF-IDF was applied to quantify term importance within a document corpus. This helped in tasks like information retrieval, text classification, and keyword extraction. For the scope of this project, the TF-IDF technique was paired with Bigram and Trigram models to get better contextual understanding of the tweets. GloVe embeddings were utilized to capture semantic relationships between words. These embeddings, derived from a large corpus, enhanced the models' understanding of text data. The models were optimized using the Stochastic Gradient Descent (SGD). This widely used algorithm efficiently updated model parameters using gradients from mini batches, which are small subsets of training data. This method helped in avoiding local minima and enhancing generalization.

For the validation of machine learning models, the "K-Fold Cross Validation" technique was applied. Data was divided into ten subsets, and the model was trained and validated ten times, with each subset used as the validation set in a different run. For BERT, the "Stratified k-fold cross-validation" was used. This method preserved the class distribution while splitting the dataset into folds for training and validation. Although the dataset was well-distributed, the consideration of future larger datasets led to the addition of the stratified k-fold feature to the BERT model's validation. The value of K for the model was set to 5.

## 4 Results and Discussion

The evaluation metrics derived from the Machine Learning models illustrated in Table 1 depict that among them, the MNB model exhibited the highest accuracy. However, it is noteworthy that the PA model outperformed MNB in terms of the F1-score, indicating its superior performance in achieving a balanced precision-recall trade-off.

Table 1: Performance Metrics of MNB and PA models

Metric	MNB TF-IDF Bigram	PA TF-IDF Bigram	MNB TF-IDF Trigram	PA TF-IDF Trigram
Accuracy	0.8003	0.7859	0.7984	0.7801
Precision	0.8586	0.7515	0.8668	0.7342
Recall	0.6406	0.7492	0.6269	0.7645
F1 Score	0.7338	0.7503	0.7275	0.7490

The evaluation metrics derived from the BERT model are illustrated in Table 2. A substantial increase in accuracy can be noted as the folds increase: from 81.77% to 94.75%.

Table 2: Performance Metrics of BERT model

Metric	Fold 0	Fold 1	Fold 2	Fold 3	Fold 4
Accuracy	0.8177	0.8531	0.8925	0.9082	0.9475
Precision	0.8173	0.8552	0.8912	0.9091	0.9501
Recall	0.8083	0.8435	0.8851	0.9025	0.9431
F1 Score	0.8115	0.8477	0.8875	0.9049	0.9462

The trade-offs between these models are significant when considering computational efficiency and applicability in real-time disaster response scenarios. Multinomial Naïve Bayes, being computationally inexpensive, offers quick training and prediction times, making it suitable for scenarios where computational resources are limited and rapid responses are crucial. However, its assumption of word independence can limit its performance on complex text data. The Passive Aggressive Classifier, while also relatively fast, provides a balance between efficiency and robustness, making it a good candidate for applications requiring online learning and continuous updates. Nevertheless, it may not capture the deep contextual nuances as effectively as neural network models. BERT, on the other hand, excels in understanding context and semantics due to its deep architecture and bidirectional attention mechanisms. This makes BERT highly effective for nuanced and complex text classification tasks. However, the computational cost of training and inference with BERT is substantially higher, requiring significant processing power and memory, which may not be feasible in real-time disaster response scenarios where quick turnaround and resource efficiency are paramount. Thus, the choice of model depends on the specific requirements of the application, balancing the need for accuracy and depth of understanding against the constraints of computational resources and response time.

All these models have also shown a similar or decent performance in other studies focused on disaster management. One such study [20] employed web scraping techniques to gather twitter data related to disasters and utilized the MNB, PA, and SVM classifiers. The MNB, PA, and SVM bi-gram models achieved respective accuracies of 80%, 78%, and 80%. Another research [21] focused on classifying relevant and irrelevant tweets concerning the 2020 Jakarta floods. The authors utilized the BERT model, and their implementation achieved 90% train and 79% test accuracies on the Indonesian Sentiment Tweet Dataset. Subsequently, they applied this model to categorize tweets related to the Jakarta floods into relevant and irrelevant classes, achieving a decent accuracy despite the presence of noise in the data. Similarly, a study [16] utilized the BERT model to classify tweets into real-disaster and non-real disaster categories. The model was trained on a dataset obtained from Kaggle named 'Natural Language Processing with Disaster Tweets' and achieved an accuracy of up to 82.55%, successfully classifying the tweets. The results clearly showcase the capabilities of models like BERT in effectively analyzing disaster-related tweets and extracting the essential information which can be used in different disaster management strategies. These models can be integrated with disaster monitoring platforms to continuously analyze tweets and other social media data streams which will facilitate real-time monitoring of the disasters, generate early warning signals, spread the information, and detect forthcoming crises. These systems can also assist disaster management authorities through prompt warning signals, allowing disaster management teams to prepare well in advance for quick response.

They can also be employed to extract information about the possible regions of impact, the severity of the disaster in a region, requests for assistance, or reports of damage and casualties in affected areas, which can be used for deploying aid according to the needs. Additionally, the models can be trained to judge false alerts, rumors, and identify misinformation to avoid unnecessary panic and provide reliable results.

## 5 Conclusion

In conclusion, this study compared three models—Multinomial Naïve Bayes, Passive-Aggressive Classifier, and BERT—for recognizing disasters in tweets. Among these models, BERT stood out as the most effective, demonstrating impressive accuracy and a high F1-score. This research highlighted the transformative potential of NLP in strengthening disaster response tactics and limiting the effects of catastrophic occurrences by applying advanced machine learning and neural network techniques.

In the future, the models can be further trained using enhanced processing hardware and expanded datasets, leading to even more accurate outcomes in practical scenarios. The utilization of the Twitter API might enable the collection of real-time data from live feeds, which can then be assessed using these advanced models. For tweets that include location details, the Google API can be implemented to determine their origins, facilitating prompt responses from governmental or disaster management authorities. Larger BERT models can be explored for yielding better results, particularly while working with more extensive datasets, if the computational capacity supports this endeavor. These potential advancements could significantly enhance disaster management strategies.

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## Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Ethical Statement

The authors confirm that all research was performed in accordance with relevant ethical guidelines and regulations. No human participants or animals were involved in this study, and all data used was publicly available.

## Data Availability Statement

The data that support the findings of this study are openly available in the Kaggle repository at <https://www.kaggle.com/competitions/nlp-getting-started/data>, reference number [Kaggle, 2021].

## Author Contributions

**Parth Mahajan:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft. **Pranshu Raghuwanshi:** Conceptualization, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft. **Hardik Setia:** Methodology, Software, Formal analysis, Investigation, Data Curation, Writing - Review & Editing. **Princy Randhawa:** Supervision, Project administration, Writing - Review & Editing.

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