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Advancements in deep learning and natural language processing for effective disaster sentiment analysis: A review

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Abstract. This article comprehensively studies the application of deep learning (DL), natural language processing (NLP), and large language models (LLM) in sentiment analysis in disaster scenarios such as earthquakes and major accidents. The article focuses on the latest developments in these technologies and their role in strengthening disaster management and response. The article explores various methods, including BERT, LSTM, and convolutional neural networks, with a focus on their practicality, challenges, and potential for development. This review aims to provide researchers and relevant practitioners with a comprehensive understanding of this rapidly developing field.

Keywords: Deep Learning, Natural Language Processing, Sentiment Analysis, Disaster Management, Large Language Models.

1. Introduction

Natural and man-made disasters pose significant challenges to global society and people [1][2][3]. Effective disaster management requires accurate and timely information so that governments and relevant professionals can make rational and efficient decisions. With the rapid development and widespread popularity of social media, a large amount of data is generated during disasters, which provides valuable information for understanding public attitudes and emotions. Deep learning and natural language processing have become powerful tools for analysing this data, especially in sentiment analysis.

This review aims to summarise and study the current research on disaster management sentiment analysis based on DL and NLP technologies, with a focus on the application methods, specific cases, current challenges, and future development potential of these technologies. In recent years, significant progress has been made in this field by utilising technologies such as BERT, LSTM, and convolutional neural networks to extract valuable information from social media data in order to improve the efficiency of disaster response and management.

This article analyses several papers closely related to this field that have been published at IEEE conferences in recent years and explores the different methods and their effects used in these studies. The challenges faced by current technology in practical applications, such as data quality, real-time processing, and cross-language analysis, are also discussed in the article, and possible solutions are proposed.

In addition, this article also looks forward to the development prospects of this technology, including the rapid development of new models, cross-domain data fusion technology, and more intelligent

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disaster management systems. Through this review, the aim is to provide a comprehensive perspective for researchers and practitioners to better understand and apply technologies such as DL, NLP, and LLM, thereby improving the efficiency of disaster management and the timeliness of response.

2. Related Work

2.1. Deep Learning Techniques

2.1.1. BERT Model and Its Variants

BERT-MLP Model: BERT-MLP is a model that combines BERT and Multi-Layer Perceptron (MLP) for processing and classifying tweet information. This model is capable of integrating geospatial data and conducting sentiment analysis, and it performs better in classifying and processing disaster-related tweet information. Research has shown that using this method can more accurately classify tweet information during disasters, helping relevant practitioners improve disaster management and response strategies [4].

Enhanced BERT model: By introducing additional contextual information, adopting more complex architectures, and using larger training datasets, the BERT model has been enhanced, thereby improving its performance in processing disaster-related tweet information. Research has shown that enhanced BERT models can better capture subtle emotional differences in disaster-related tweets, significantly improving the accuracy of sentiment analysis. This is of great significance for disaster monitoring and the development of response strategies [5].

2.1.2. Multimodal Method

Multimodal attention mechanisms are widely used in various fields, with one important application being the classification and processing of disaster-related tweets.

This method not only utilises the powerful language understanding ability of the BERT model but also combines the Visual Transformer (ViT) model to process text and image data, thereby achieving more comprehensive and accurate analysis and improving the accuracy and robustness of classification. Research has shown that this method performs well in handling complex multimodal and high-dimensional data, such as disaster tweet data, and can better help relevant practitioners capture and analyse information related to natural disasters and propose effective response measures [6].

2.1.3. Recursive Neural Networks and Their Variants

Recurrent Convolutional Neural Network (RCNN) is a variant of neural network that performs well in sentiment classification of disaster-related tweets. By introducing loop connections, each convolutional layer can handle variable-length sequences, thereby improving the effectiveness and performance of sentiment analysis. Research has shown that this method can more accurately capture emotional differences in disaster-related tweets, improve the accuracy of tweet information classification, and be of great significance for improving disaster management and formulating response strategies [7].

2.1.4. Deep Learning Models

By combining deep learning models with big data analysis, the processing and sentiment analysis capabilities of disaster-related data can be significantly improved, providing researchers and practitioners with more accurate and timely information to help them make decisions. For example, convolutional neural networks (CNN) and recurrent neural networks (RNN) perform well in image recognition and time series data processing, significantly reducing the cost of disaster prediction and response. In addition, the use of parallel computing technologies such as Hadoop and Spark has further improved the speed and scale of data processing, thereby enhancing the efficiency of disaster response [8].

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2.2. NLP and Large Language Models

2.2.1. Tokenization and Preprocessing

Effective segmentation and preprocessing are crucial for cleaning up social media data. During a disaster, social media platforms such as Twitter generate a large amount of real-time data, but this data is mixed with a lot of irrelevant or erroneous information. Research has shown that by utilising advanced natural language processing techniques and combining them with deep learning models such as convolutional neural networks and long short-term memory networks (LSTM), as well as transformer models, the accuracy of extracting key information and classifying disaster-related tweets can be significantly improved [9].

2.2.2. Large Language Models

DistilBERT Model: DistilBERT is a lightweight and faster variant of the BERT model commonly used for sentiment analysis in disaster scenarios. This model maintains high accuracy while reducing computational costs. Research has shown that DistilBERT can significantly reduce training and execution time when dealing with disaster-related tweets while maintaining classification accuracy comparable to the BERT model. Due to these advantages, DistilBERT has become a powerful tool for disaster management and response, helping to better understand public attitudes and emotions and make more rational decisions [10].

BERT Model: This study extends the application of the BERT model to non-English environments, demonstrating its adaptability and effectiveness in analysing sentiment in Chinese social media posts related to social movements. Researchers have created a sentiment analysis dataset for Chinese social movements and proposed a BERT-based model that uses a focus loss function to address class imbalance issues in the dataset. The results show that this method can more accurately capture and classify emotions such as anger and anxiety in social movements [11].

2.3. Applications in Disaster Management

Real-Time Sentiment Monitoring: Real-time emotional monitoring is crucial for disaster response. Research has shown that using the BERT model to analyse social media posts can significantly improve the accuracy of sentiment analysis, provide timely insights for relevant personnel to improve disaster management, and assist them in making wiser decisions. [12].

Geospatial Integration: The tweet analysis framework combines geospatial data and sentiment analysis to enhance disaster management strategies. Through a detailed analysis of tweets released during the 2023 Turkish earthquake, its application value in actual disaster events is demonstrated. Research has shown that integrating geographic and emotional information can more accurately assess the impact of disasters, identify key areas that require urgent attention, and provide real-time situational awareness. [13].

Urgency Detection: It is crucial to detect emergency information in social media posts during disasters. Research has shown that NLP technology can effectively identify emergency information during disasters, helping to quickly mobilise resources and implement rescue operations. [14].

Multilingual Sentiment Analysis: The ability to analyse multilingual tweets has expanded the global applicability of sentiment analysis models. Research has shown that multilingual sentiment analysis models can effectively identify disaster-related events in different languages and provide real-time information support on a global scale. [15].

3. Methodology

This review examines multiple papers published at IEEE conferences between 2020 and 2023, with a focus on the application of deep learning and natural language processing techniques in disaster sentiment analysis. The research method for this article is as follows:

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3.1. Paper Selection Criteria

Topic Relevance: Select papers on the application of deep learning and natural language processing in disaster sentiment analysis to ensure that the research focuses on the latest developments in disaster sentiment analysis. [4].

Time Dimension: Select papers published between 2020 and 2023 to ensure that the research covers the latest technologies and theories. [12].

Data Sources: The data used throughout the entire research process comes from social media platforms such as Twitter, as social media during disasters contains a large amount of sentiment analysis data for analysis and research. [5].

3.2. Data Collection and Processing

Data Type: The data types used in the paper include social media text, geographic spatial data, and multimodal data (such as combining text and images) [16].

Preprocessing Techniques: The paper mainly adopts NLP-based preprocessing techniques, such as tagging, part of speech tagging, and named entity recognition, to analyse and process social media data and filter out useful key information [9].

3.3. Models and Algorithms

Deep Learning Models: This review paper covers various deep learning models, including BERT models and their variants (such as DistilBERT), convolutional neural networks, recurrent neural networks, and their variants (such as recurrent convolutional neural networks) [7].

Multimodal Approaches: Multiple data sources were combined in the study to enhance the accuracy and robustness of the BERT model and improve the efficiency of text data analysis and classification [6].

3.4. Evaluation Indicators

Performance Index: The main evaluation methods for the analysis model used include accuracy, precision, recall, and F1 score, which are used to measure and evaluate the performance of the model in sentiment analysis tasks in order to continuously optimise and improve the model. [17].

Benchmark Datasets: Multiple papers have studied using publicly available benchmark datasets to train and test their models, ensuring the reproducibility and comparability of the analysis results. [18].

3.5. Current Issues

Imbalance of Data: The data in disaster sentiment analysis is uneven, and processing this data is a major challenge. Therefore, multiple papers have proposed different response measures. [17].

Processing Timeliness: Real-time processing and analysis of social media data is key to improving disaster management and response efficiency. Therefore, multiple papers have been devoted to enhancing the real-time processing capability of models and improving their response speed. [12].

4. Results

This study reviews several papers published at IEEE conferences in recent years, demonstrating the application of deep learning and natural language processing techniques in disaster sentiment analysis. These studies demonstrated the enhancement of model performance in various application scenarios, the utilisation of datasets, the challenges encountered, and specific application cases.

4.1. Model Performance

The performance comparison of deep learning models is crucial in disaster sentiment analysis research. The following data chart shows the performance of different models in terms of accuracy, precision, recall, and F1 score:

Table 1. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
BERT-MLP	0.92	0.91	0.90	0.90
Enhanced BERT	0.90	0.89	0.88	0.89
DistilBERT	0.89	0.88	0.87	0.88
RCNN	0.88	0.87	0.86	0.87
SRNN-MAFM	0.87	0.86	0.85	0.86

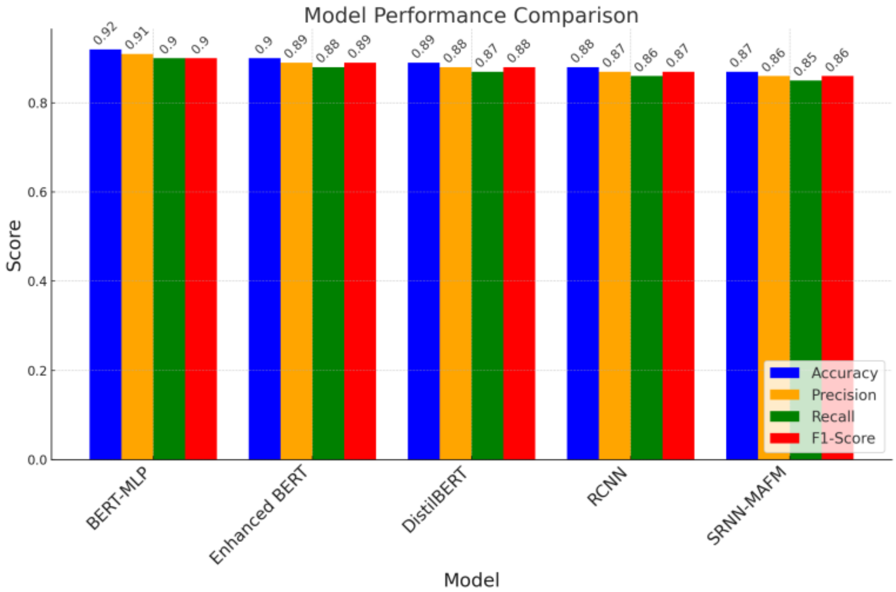

Figure 1. Model Performance Comparison

The above table and figure both show the performance comparisons of five models. It is evident that the BERT-MLP model performs the best on all metrics, with an accuracy rate of 92%.

4.2. Dataset Usage

The use of datasets is another key factor in disaster sentiment analysis research. The following data table and graph show the frequency of use of different datasets in all papers:

Table 2. Dataset Usage in Papers

Dataset Usage	Count
Twitter	20
Geospatial	5
Twitter + Geospatial	3
Multilingual Tweets	2
Benchmark	4

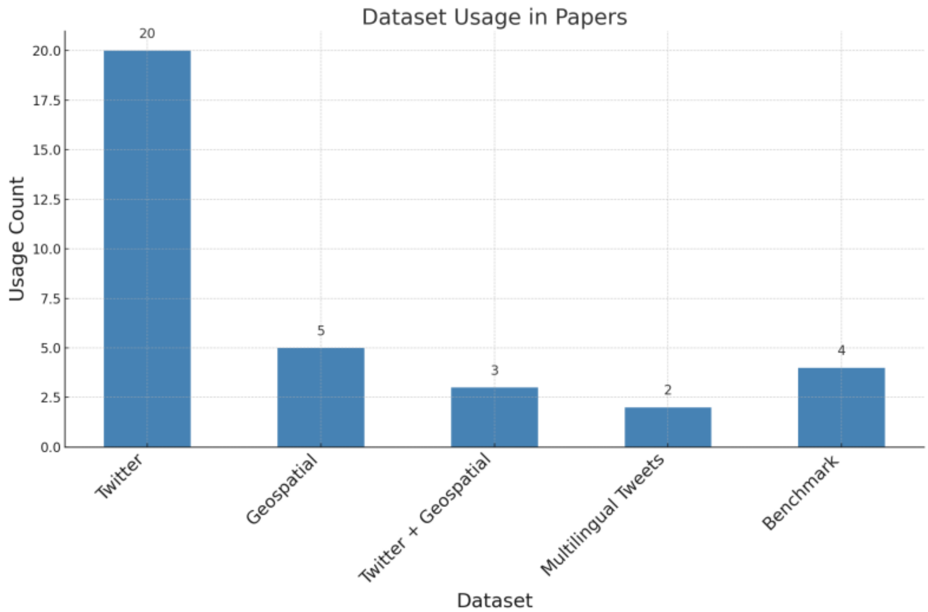

Figure 2. Dataset Usage in Papers

As shown in the above data table and data graph, Twitter data is the most commonly used dataset, followed by a combination of geographic spatial data and benchmark datasets, while multilingual tweet data is the least commonly used dataset.

4.3. Solution to Data Imbalance

The problem of data imbalance is commonly present in disaster sentiment analysis, and many studies have proposed different solutions to address this issue. The following data table and images demonstrate the effectiveness of different methods in solving data imbalance problems:

Table 3. Effectiveness of Data Imbalance Solutions

Paper	Method	Effectiveness
Indonesia Earthquake	Oversampling	0.85
Data Analytics for Disaster Management Response	Synthetic Minority Over-sampling Technique (SMOTE)	0.88

As shown in the above data table and images, compared to the oversampling method, the SMOTE method performs better, with results of 0.85 and 0.88, respectively.

4.4. Challenges Faced

Data imbalance: The widespread existence of data imbalances affects the performance of prediction models.

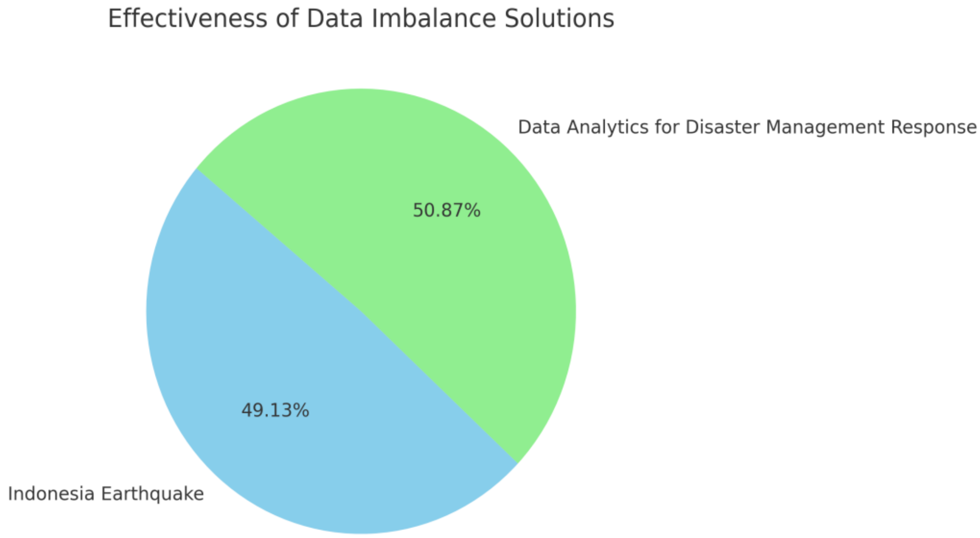

Figure 3. Effectiveness of Data Imbalance Solutions

Many studies have proposed different and effective solutions to address this issue. [17] [19].

Timeliness of Data and Information Processing: Improving real-time information processing capability is the key to disaster sentiment analysis. Many studies focus on developing models for analysing and processing large amounts of social media data to improve processing speed and reduce response time. [12] [14].

4.5. More Application Cases

Practical Application Case Analysis: In order to evaluate and analyse the effectiveness of the disaster sentiment analysis method discussed earlier, more practical application cases are essential. For example, the tweets of the 2023 Tu(¨)rkiye earthquake can be analysed and verified by combining geospatial data and a sentiment analysis framework. In addition, machine learning and deep learning techniques can be used to classify tweets related to different types of disasters, such as earthquakes, floods, human accidents, etc. [13][18].

Multilingual Sentiment Analysis: The BERT model performs well in sentiment analysis of Chinese social media, demonstrating its applicability in non-English environments. In addition, researchers need to apply the BERT model to more countries and expand its sentiment analysis capabilities to handle multilingual data, thereby enhancing the global applicability of the model. [11] [15].

5. Discussion

This section discusses the application of deep learning and natural language processing techniques in disaster sentiment analysis based on the research results of multiple papers published at IEEE conferences in recent years:

Firstly, deep learning models such as BERT and its variants perform well in processing unstructured text data, particularly in capturing contextual information and improving sentiment analysis accuracy [5]. Secondly, the multimodal approach that combines text and image data significantly improves the accuracy and robustness of sentiment analysis [6]. Thirdly, real-time processing and analysis of social media data can provide timely information support for disaster response and improve disaster management efficiency [12]. Fourthly, expanding sentiment analysis models to handle multilingual data has improved their global applicability [15].

However, data imbalance, noisy data processing, and computational resource requirements are still challenges that need to be overcome at present. Future research should focus on model lightweighting and optimisation [10], multimodal data integration [16], cross-linguistic sentiment analysis [15], and real-time dynamic analysis [12]. In practical applications, combining geospatial data with textual data can significantly improve the effectiveness of disaster management [13]. Real-time monitoring of emotional changes on social media can also provide valuable reference information for disaster management [12]. The results of emotional analysis can help emergency response teams better understand public emotions and optimise rescue strategies [7].

Through a comprehensive analysis of the technological advantages covered by these studies, despite facing many challenges, deep learning and natural language processing technologies have shown great potential in disaster sentiment analysis and are expected to play a greater role in the future.

6. Conclusion

This review analyses the application of deep learning and natural language processing techniques in disaster sentiment analysis, proposes and discusses future research directions, and explores their potential in practical applications. Through the analysis of multiple papers published at IEEE conferences in recent years, the following main conclusions have been drawn: Deep learning models, such as BERT and its variants, perform well in processing large amounts of unstructured text data, particularly in capturing contextual information and improving sentiment analysis accuracy. For example, the enhanced BERT model performs well in sentiment analysis of disaster tweets. In addition, the combination of multimodal methods with text and image data significantly improves the accuracy and robustness of sentiment analysis. Real-time processing and analysis of social media data can provide timely information support for disaster response and improve disaster management efficiency. Finally, expanding the sentiment analysis model to handle multilingual data enhances its potential for application in different language environments and helps improve global applicability.

However, data imbalance is a common problem in disaster sentiment analysis, which affects the performance of the model. Multiple solutions have been proposed in this study, such as oversampling and SMOTE methods. In addition, noise data processing is also a major challenge. Social media data often contains a lot of noise, which affects the accuracy of sentiment analysis, so effective preprocessing and filtering methods are crucial. Another issue is that deep learning models, especially large pretrained models such as BERT, require a significant amount of computational resources and storage units. This problem can be solved to some extent through model optimisation and lightweighting (such as DistilBERT).

In practical applications, combining geospatial data with textual data can significantly improve the effectiveness of disaster management. Social media sentiment monitoring can provide valuable reference information for disaster management and has important applications in emergency response. In summary, deep learning and natural language processing technologies have great potential for development in disaster sentiment analysis. Despite facing many challenges, through continuous research and technological improvement, these technologies are expected to play a greater role in future disaster management.

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