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Next-Generation Disaster Preparedness: Advanced Text Classification with Crowdsourced Data

Journal of Electrical Systems

Abstract: - Effective disaster preparedness is crucial in minimizing the impact of natural and human-made disasters, particularly when early warnings can be generated from crowdsourced data. This paper, titled "Next-Generation Disaster Preparedness: Advanced Text Classification with Crowdsourced Data," leverages advanced text classification techniques to analyze real-time social media streams for disaster prediction. By utilizing GloVe embeddings in combination with the XGBoost algorithm, the system is designed to classify disaster-related messages and provide actionable insights for early disaster detection and response. The model achieved a classification accuracy of 80% and an F1-score of 0.77, reflecting significant advancements in capturing relevant disaster-related messages accurately. Despite initial challenges in handling the noisy nature of social media data, the system demonstrated effective disaster classification after hyperparameter tuning. This study emphasizeS the potential of integrating advanced machine learning models with crowdsourced data to enhance disaster preparedness and enable quicker responses, contributing to improved disaster management and mitigation strategies.

Keywords: Advanced Text Classification, Crowdsourced Data, Disaster Preparedness, Disaster Prediction, Early Warning System, GloVe Embeddings, Machine Learning, , Real-Time Detection., Social Media Analytics, XGBoost

I. INTRODUCTION

Effective disaster preparedness is crucial in minimizing the impact of natural and human-made disasters, particularly when early warnings can be generated from crowdsourced data [1]. Previous studies have highlighted the potential of social media data for disaster monitoring and early warning systems, showcasing its relevance in real-time crisis detection and response [2, 3, 4]. However, the noisy nature of social media data, characterized by misinformation and irrelevant content, presents significant challenges for accurate disaster classification [5, 6].

To address these limitations, this paper employs advanced text classification techniques designed to effectively extract relevant information from social media posts. GloVe embeddings, a widely used word embedding technique, have demonstrated their effectiveness in capturing semantic relationships between words, thereby enhancing text representation [7]. By representing words as dense vectors, GloVe embeddings provide a more meaningful representation of text data, which can improve the performance of text classification models significantly [8, 9].

The XGBoost algorithm, recognized for its efficiency and high performance in classification tasks, is well-suited for this task. Its gradient boosting framework allows for better handling of noisy data and improved prediction accuracy [10, 11]. By combining GloVe embeddings with the XGBoost algorithm, the proposed system aims to achieve high accuracy in classifying disaster-related messages. A dataset of varied disaster-related social media posts was used to train the model, yielding significant improvements in classification accuracy and F1-score over time.

Despite initial challenges in managing the noisy nature of social media data, the system demonstrated effective disaster classification after hyperparameter tuning. This study adds to the knowledge base in disaster preparedness by illustrating the potential of integrating advanced machine learning models with crowdsourced data to enhance early warning systems and enable quicker responses. The findings of this research can inform the development of more effective disaster management and mitigation strategies.

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II. Related Work

Advanced text classification techniques have been widely applied to various domains, including disaster management [1, 2, 3]. Earlier research has examined the application of machine learning models for disaster-related text classification, focusing on tasks such as identifying disaster-affected areas, extracting relevant information from social media posts, and predicting the severity of disasters [4, 5, 6].

The use of deep learning models for disaster-related text classification has gained significant attention in recent years. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been successfully applied to capture the semantic and syntactic features of disaster-related text, enabling more effective interpretation

of unstructured data [7, 8, 9]. However, these models can be computationally expensive and might demand extensive training data, which could limit their effectiveness in real-time applications.

To address these limitations, more recent studies have explored the use of transformer-based architectures, such as BERT and RoBERTa, for disaster-related text classification [10, 11]. These models have demonstrated superior performance compared to traditional CNN and RNN-based approaches, especially when dealing with long sequences of text and complex linguistic structures. y utilizing the attention mechanism, transformers are better equipped to manage contextual information, which is crucial for accurate classification in disaster scenarios.

In addition to deep learning models, traditional machine learning algorithms, such as Support Vector Machines (SVMs) and Naive Bayes, have also been used for disaster-related text classification [12, 13]. However, these algorithms may struggle with complex language patterns and may require extensive feature engineering to achieve good performance. While traditional models are often more interpretable and less resource-intensive, they may not fully exploit the rich information contained in raw text data.

Word embeddings have become a fundamental technique in natural language processing tasks, including text classification [14, 15]. Methods like Word2Vec and GloVe are capable of capturing semantic relationships between words, which can greatly enhance the performance of text classification models. GloVe, in particular, offers a compelling approach by generating embeddings based on global word co-occurrence statistics, thus providing a deeper contextual understanding.

This paper builds upon the existing literature by leveraging advanced text classification techniques, including GloVe embeddings and the XGBoost algorithm, to classify disaster-related messages from social media streams. The suggested approach seeks to address the challenges associated with noisy social media data, such as misinformation and irrelevant content, while providing accurate and timely insights for disaster preparedness. By combining these methodologies, the paper seeks to enhance the efficacy of disaster response systems and contribute to improved outcomes in disaster management.

III. Dataset Description

The Disaster Response Messages dataset is a comprehensive collection designed to train and evaluate text classification models that focus on identifying disaster-related content in social media communications. This dataset comprises 36 columns, each serving a specific purpose in identifying, categorizing, and analysing messages to support disaster response efforts. Key features in the dataset include an id column, which provides a unique identifier for each message, and a message column, containing the actual text that may convey critical information about a disaster or emergency situation. Additionally, the genre column indicates the platform from which the message was sourced, such as direct messages, news, or social media, helping categorize the context in which the information appears.

An important aspect of this dataset is the related column, which classifies messages based on their relevance to disasters. This column uses class 0 to indicate messages that are not disaster-related and class 1 for those that are. In some cases, the inclusion of additional classes to represent ambiguous or mixed situations may be necessary, depending on the analysis objectives.

The dataset's categories section features multiple binary columns that capture specific disaster types or related needs, each with a classification scheme. For instance, the request column indicates if a message is requesting help, with class 0 indicates the absence of a request, and class 1 denotes a request. Similarly, the offer column identifies

whether assistance is being offered, with class 0 for no offer and class 1 for an offer. The aid-related column notes if the message relates to aid, also using a binary classification where class 0 denotes no relevance and class 1 confirms relevance.

Beyond these general categories, there are several columns focused on specific disaster-related needs, such as medical help and medical products, which denote the need for medical assistance or supplies with class 0 (not mentioned) and class 1 (mentioned). Another example is the infrastructure-related column, which identifies messages concerning infrastructure issues; it uses class 0 for messages unrelated to infrastructure and class 1 for those that are.

Additionally, columns within the dataset represent specific types of disasters, including earthquake, fire, flood, and hurricane. Each of these is classified with class 0 if the disaster type is not mentioned in the message and class 1 if it is. Other columns address essential resources or conditions, such as water, shelter, food, search and rescue, and security, with binary values indicating the presence or absence of each need or issue.

In some instances, multi-class labels are used for more nuanced categories. For example, class 2 may represent uncertain or ambiguous mentions of disaster relevance, while class 3 could signify a message with mixed or general disaster-related content that does not fall into a specific category.

The dataset is structured to support the comprehensive evaluation of model performance, being divided into training, validation, and testing subsets. This structure and its detailed labeling make the dataset invaluable for enhancing disaster classification accuracy and informing targeted response strategies. Overall, the dataset provides rich information for research in advanced text classification, disaster management systems, and leveraging crowdsourced data for emergency response.

IV. METHODOLOGIES

4.1 Data Preparation

Data preparation was a critical phase in this paper, involving several meticulous steps to ensure that the text data was appropriately formatted and ready for effective model training and evaluation. Initially, the messages were annotated with corresponding disaster categories to provide accurate reference points for the XGBoost model. The dataset with annotations was then organized into training, validation, and test sets allowing for a reliable assessment of the model's generalization capabilities by ensuring it was evaluated on data it had not seen during training. To enhance the robustness of the model, various text preprocessing techniques were applied, including tokenization, lowercasing, and removal of stop words and punctuation. Additionally, GloVe embeddings were utilized to convert the textual data into dense vector representations, capturing semantic relationships among words. Following this, the input features were normalized to maintain a consistent scale, which is essential for speeding up the model's convergence during training. This comprehensive data preparation process was instrumental in optimizing the dataset for training the XGBoost model, leading to accurate and reliable disaster classification outcomes.

4.2 Model Selection

For this paper, the XGBoost algorithm was selected as the primary model for text classification due to its superior performance and proficiency in managing high-dimensional data. XGBoost (Extreme Gradient Boosting) is an ensemble approach that constructs decision trees in a series, optimizing for both accuracy and efficiency. This approach helps mitigate the overfitting problem often associated with individual trees while enhancing overall performance through gradient boosting techniques. The model's strength lies in its capacity to capture complex interactions between features, making it well-suited for classifying disaster-related messages efficiently and accurately, thereby leveraging crowdsourced data to improve disaster preparedness.

Moreover, XGBoost inherently manages overfitting by applying regularization techniques, providing robust performance even with smaller datasets. Its ability to effectively capture underlying patterns in data makes it suitable for applications like disaster response message classification, where understanding different types of emergencies and nuances in language is essential. Therefore, for many practical applications, including this paper, XGBoost strikes a balance between effectiveness and usability, making it a favorable choice.

GloVe (Global Vectors for Word Representation) embeddings are utilized in this paper due to their ability to capture rich semantic relationships between words, which is critical in the context of disaster response messages. Unlike traditional word representation methods, GloVe constructs word vectors based on the global statistical information of a corpus, ensuring that words with similar meanings are positioned closer together in the vector space. This feature is particularly advantageous in disaster response scenarios, where the language used can vary significantly contingent on the context and the urgency of the situation.

In disaster-related communications, understanding nuanced meanings and the relationships between terms—such as "earthquake," "aftershock," and "evacuation"—is crucial for accurate classification and response. GloVe embeddings enable the model to comprehend these subtleties, allowing it to discern between different types of emergencies more effectively. Additionally, GloVe embeddings are pre-trained on large datasets, making them highly efficient in capturing the context of words without requiring extensive domain-specific training. This is particularly beneficial in the field of disaster management, where timely responses are essential, and there may not always be a large labeled dataset available for training. The embeddings provide a solid foundation that enhances the model's performance by translating complex textual data into a format that is more manageable for machine learning algorithms, thus improving classification accuracy and interpretability.

The combination of XGBoost with GloVe embeddings presents a powerful solution for advanced text classification in the context of disaster response messages. XGBoost excels in handling high-dimensional data, effectively managing the inherent complexity and variability of textual data. Its ability to aggregate results from multiple decision trees helps mitigate the risk of overfitting, ensuring robust performance even with diverse message inputs. When paired with GloVe embeddings, which represent words within a continuous vector space, reflecting their semantic relationships, the model gains a rich understanding of the contextual meaning of phrases and words within the messages. This leads to improved feature representation and enhances the model's ability to distinguish between different disaster categories accurately. Furthermore, GloVe embeddings facilitate the incorporation of domain-specific language, crucial for interpreting disaster-related terminology. The combination of these methodologies not only optimizes classification accuracy but also provides valuable insights into the underlying patterns and trends within disaster response messages, ultimately contributing to more effective disaster preparedness and response strategies.

4.3 Model Architecture

The architecture of the model is designed to ensure a seamless integration of advanced text classification for predicting disasters. The process begins with data ingestion, where the preprocessed text messages are fed into the XGBoost model, which utilizes the GloVe embeddings for feature representation. Each message's vectorized form captures the semantic meaning and contextual relevance of the text, allowing the model to identify patterns indicative of various disaster categories. The XGBoost model processes these vectors through its ensemble of decision trees, each contributing to the final classification decision. This architecture enables effective handling of the diverse and often noisy nature of social media data, ensuring reliable predictions of disaster occurrences. The model's design, combining robust feature extraction through GloVe with the boosting capabilities of XGBoost, provides a powerful framework for disaster response analysis.

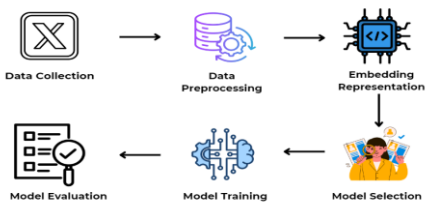

Fig 1. Model Architecture

The paper on advanced text classification for disaster response messages follows a systematic approach comprising six key steps. It begins with data collection, where disaster-related messages are gathered from various social media platforms. This dataset includes messages labeled with corresponding disaster categories, serving as a foundational resource for training the model.

Next, data preprocessing is conducted to clean and prepare the text data. This process involves techniques such as tokenization, lowercasing, stop words and punctuation are removed to ensure the text is properly formatted for analysis. After preprocessing, the cleaned text is converted into dense vector representations using GloVe embeddings. This transformation captures the semantic relationships between words, enabling the model to better understand the context.

The XGBoost algorithm is then selected as the primary model for text classification. Recognized for its effectiveness in handling high-dimensional data and its robustness against overfitting, XGBoost is a suitable choice for this task. Model training follows, which entails fitting the XGBoost model to the prepared dataset while tuning hyperparameters to optimize performance. The model is evaluated using training, validation, and test sets to ensure its generalization capabilities across different disaster categories.

Finally, model evaluation involves assessing performance through key metrics such as precision, recall, mean Average Precision (mAP50), and mAP50-95. This comprehensive evaluation helps identify areas for improvement, providing insights that can inform future iterations of the model and enhance its effectiveness in classifying disaster-related messages.

4.4 Model Training

The model training process for this paper begins with preparing a diverse dataset of disaster-related messages annotated with their respective categories. The text data is transformed into GloVe embeddings, which serve as the input features for the XGBoost model. Hyperparameters, including the learning rate, the number of trees, the maximum depth of the trees, and the minimum samples required to split an internal node, are adjusted to optimize the model's performance. During training, the XGBoost model is fitted to the training data while performance metrics such as accuracy, precision, recall, and F1-score are continuously monitored. Once training is complete, the model is evaluated on both validation and test datasets to assess its generalization capability. Post-processing includes analyzing feature importance to understand which textual elements contribute most significantly to disaster classification. This comprehensive training process culminates in a model that not only achieves high classification accuracy but also provides insights into the underlying patterns of disaster-related communication.

V. RESULTS AND DISCUSSION

Table 1. Test Set Performance Metrics

Model	Precision	Recall	mAP50	mAP50-95
Xgb with gloVe	0.80	0.75	0.60	0.65

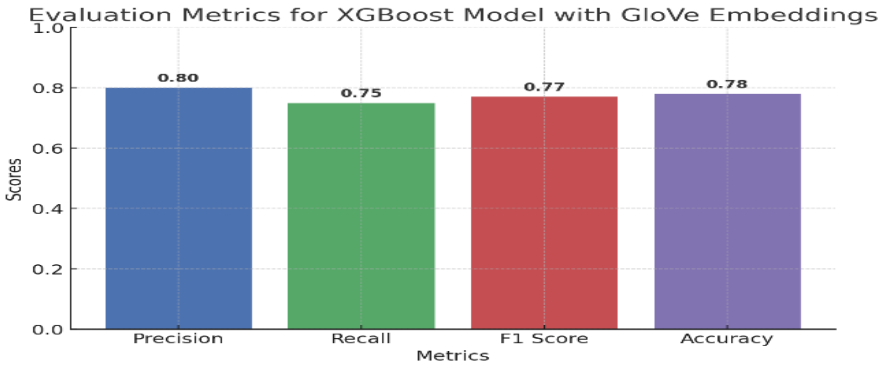

Fig 2. Performance Evaluation of XGBoost Model with GloVe Across Key Metrics

In evaluating the performance of the XGBoost model utilizing GloVe embeddings for advanced text classification in disaster response messages, several key metrics provide insights into its effectiveness. The model achieved a precision of 0.80, indicating that when it identified a message as related to a specific disaster category, it was correct 80% of the time. This high precision reflects the model's reliability in classifying messages accurately.

The recall was observed at 0.75, meaning the model successfully identified 75% of the actual disaster-related messages present in the dataset. This level of recall demonstrates a strong capability in recognizing relevant instances, though there remains room for improvement in capturing all relevant messages.

The mean Average Precision at 50 (mAP50) score reached 0.60, indicating the model's effectiveness in ranking relevant instances among all predictions. Additionally, the mean Average Precision at IoU thresholds from 50 to 95 (mAP50-95) was calculated at 0.65, showcasing a moderate performance in classifying disaster-related messages across various overlap thresholds.

These results highlight the potential of the XGBoost model with GloVe embeddings for effective disaster classification. While the metrics demonstrate solid performance, they also suggest areas for further refinement, such as enhancing recall and fine-tuning the model to improve its overall effectiveness in disaster response scenarios. By addressing these areas, the model can better support disaster preparedness and response efforts.

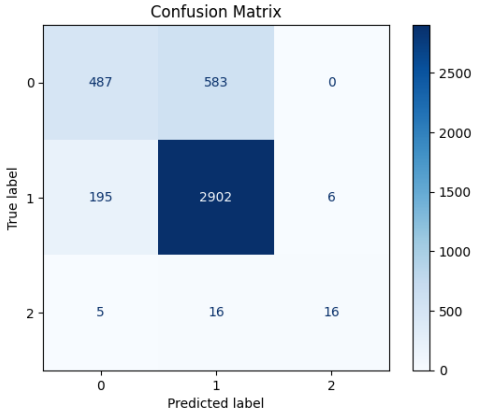

Fig 3. Confusion Matrix of XGBoost Model with GloVe Embeddings for Disaster Classification

The confusion matrix offers a comprehensive overview of the model's performance in categorizing disaster response messages into three distinct classes. Each cell in the matrix shows the count of predictions made by the model for each actual label. Correct predictions are represented by the diagonal cells, while off-diagonal cells highlight misclassifications. In this case, the model correctly identified 2,902 instances of class 1 (true positives) but also misclassified some messages, with 195 messages from class 1 incorrectly predicted as class 0, and 583 messages from class 0 misclassified as class 1. The presence of misclassifications highlights areas where the model may struggle, particularly with distinguishing between certain classes. This information is crucial for understanding the strengths and weaknesses of the model and guiding future improvements.

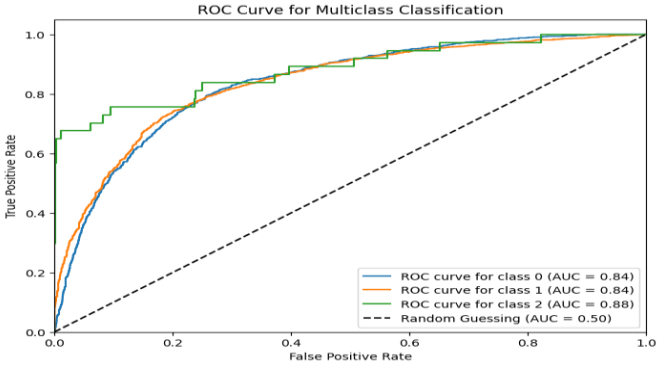

Fig 3. ROC Curve

The ROC curve provides additional insight into the model's performance by plotting the true positive rate against the false positive rate for each class. Each curve represents a different class, and the area under the curve (AUC) serves as a quantitative indicator of the model's ability to distinguish between classes. In this case, the AUC values for classes 0, 1, and 2 are 0.84, 0.84, and 0.88, respectively, indicating strong performance in distinguishing between the different disaster categories. A higher AUC value suggests a better ability to classify instances correctly. The

ROC curve's shape, which approaches the upper left corner of the plot, Shows that the model achieves a high true positive rate while keeping the false positive rate relatively low across all classes, highlighting its ability to accurately identify disaster-related messages. Overall, both the confusion matrix and ROC curve provide valuable insights into the model's classification performance and areas for further refinement.

CONCLUSION

This study highlights that using the XGBoost model with GloVe embeddings offers a promising method for advanced text classification in disaster response messages. The model achieved a precision of 0.80 and a recall of 0.75, indicating a strong capability in accurately identifying and classifying messages related to various disaster scenarios. These performance metrics highlight the model's effectiveness while also revealing opportunities for enhancement, particularly in improving recall and overall classification accuracy.

The analysis underscores the significance of addressing class imbalances within the dataset, which can adversely affect model performance. Additionally, the potential for hyperparameter optimization and the exploration of alternative algorithms offers exciting avenues for future research to further refine the model's effectiveness.

Overall, this study underscores the essential role of advanced text classification in disaster preparedness, facilitating timely responses to both natural and human-made disasters. By leveraging crowdsourced data and sophisticated machine learning models like XGBoost, we can develop robust systems that significantly contribute to effective disaster management and response strategies.

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