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OPTIMIZING EMERGENCY RESPONSES VIA DISASTER LSTM ALGORITHM FOR SOCIAL MEDIA ANALYSIS

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ABSTRACT

The increasing frequency of natural disasters demands efficient and accurate classification systems for real-time information dissemination. This study develops and evaluates classification systems for tweets related to six disaster types—hurricane, forest fire, tornado, drought, flood, and fire—aiming to enhance disaster response capabilities through improved classification accuracy and sentiment analysis. The study uses a dataset of labeled tweets, incorporating both disaster type and sentiment labels (positive, negative, neutral) to assess public reactions. By integrating sentiment analysis into the classification process, emergency responders can identify disaster events and gauge the emotional tone of the population in real-time, providing crucial insights for better decision-making.

Two models were implemented: a K-Nearest Neighbors (KNN) algorithm and a Disaster Long Short-Term Memory (DLSTM) network. The KNN algorithm, used as a baseline, showed adequate performance but struggled with the complexities of sequential text data and sentiment analysis. In contrast, the Disaster LSTM model, which utilized both disaster classification and sentiment analysis, significantly outperformed KNN. It achieved an overall accuracy of 84.0%, with 87.2% for hurricanes and 81.9% for droughts, while also demonstrating strong performance in sentiment classification.

The novelty of this study lies in its dual-focus model, which simultaneously classifies disaster types and associated sentiments using a fine-tuned LSTM network. This integrated approach offers a more comprehensive understanding of real-time public discourse during disasters—unlike prior studies that addressed these aspects in isolation. These improvements enable faster disaster identification, more efficient resource allocation, and a better understanding of public emotions during crises. This research contributes to the fields of natural language processing and disaster management by constructing a robust framework for leveraging social media data for real-time situational awareness and emergency response.

Keywords: *Disaster Response, Disaster Long Short Term Memory, Tweet Classification, Real-Time Information, Natural Language Processing, Deep Learning, Social Media Data*.

1. INTRODUCTION

This study aims to develop a real-time tweet classification model for disaster types and associated sentiments using a fine-tuned LSTM approach, contributing novel methods for emergency preparedness. The key assumption is that Twitter data is representative of real-time disaster indicators. The study's limitations include language coverage, informal and noisy text formats, and limited ground truth availability for certain disaster categories—particularly for droughts, forest fires, and fires—which tend to be underrepresented in the collected dataset compared to more frequently reported disasters like hurricanes and floods.

Natural disasters are the most importance challenge of the people of the 21st century. With increasing frequency as well as severity, events such as hurricanes, forest fires, tornadoes, droughts, floods, and fires devastate communities, disrupt economies, and strain resources globally. These disasters not only cause immediate loss of life and property but also leave lasting impacts on infrastructure, health systems, and the environment. The frequency and intensity of

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natural disasters are influenced by a complex interplay of factors, including climate change, urbanization, population growth in vulnerable areas, and inadequate disaster preparedness and response strategies. The urgency of effective disaster response and management has never been more apparent. Timely and accurate dissemination of information is crucial in mitigating the impact of disasters, enabling swift evacuation, delivering aid to affected populations, and coordinating rescue and resettlement activities. In these years, social networking sites have grown as critical medium in disaster response because of their capability of transmitting current up to date updates, facilitate communication among stakeholders, and mobilize support globally. Among these platforms, Twitter has gained prominence for its widespread adoption, immediacy, and capacity to disseminate concise messages rapidly.

During disaster events, Twitter serves as a dynamic information ecosystem where individuals, organizations, and governments share situational updates, issue alerts, request assistance, and provide firsthand accounts of unfolding events. The platform's capability to transmit information quickly and reach a vast audience has transformed how emergency responders and the public perceive and respond to disasters. However, the sheer volume of data generated on Twitter during crises poses significant challenges in effectively extracting, analyzing, and utilizing pertinent information for disaster response purposes. Machine learning (ML) and deep learning (DL) methods gives us the reliable solutions to address these challenges by automating the classification, analysis, and interpretation of large-scale social media data. These techniques enable the development of sophisticated algorithms capable of categorizing tweets into specific disaster types, identifying critical trends and patterns, and enhancing the effectiveness of information processing and decision-making during disaster events.

This study focuses on evaluating the effectiveness of two distinct classification models— the K-Nearest Neighbors (KNN) technique and a improved Long Short-Term Memory (LSTM) network— in categorizing disaster-related tweets. The KNN algorithm, a traditional ML method, classifies data points based on proximity to neighboring points in feature space. Compared to the LSTM network, a type of recurrent neural network (RNN), excels in operating on the conituous data and records long-term dependency, making it well-suited for analyzing temporal patterns and context in tweet sequences during disasters. The dataset utilized in this research comprises tweets annotated with six distinct disaster types: hurricanes, forest fires, tornadoes, droughts, floods, and fires. Each tweet is manually labeled with its corresponding disaster category, providing ground truth labels for training of the model, validation, and examination. By comparing the effectiveness of the KNN algorithm and the Disaster LSTM network across many performance indicators like precision, accuracy, F1-score and recall this paper focuses to ascertain which approach demonstrates superior capability in classifying disaster-related tweets accurately and efficiently.

The conclusion of this paper hold important applications for advancing disaster response as well as management practices. By identifying the most effective classification model for analyzing social media data during disasters, this paper can play vital role to the advancements of many robust and adaptive disaster response applications. Improved classification accuracy enables quicker detection and classification of disaster-related information, enhances situational awareness among emergency responders, and facilitates targeted allocation of resources and aid to affected areas.

Moreover, enhancing the effectiveness of social media analytics in disaster response can potentially transform global emergency preparedness efforts. By harnessing the power of ML and DL techniques, governments, humanitarian organizations, and disaster response agencies can leverage real-time social media data to enhance decision-making, improve resource allocation, and ultimately save lives in disaster-affected communities worldwide.

In the subsequent sections, detailed methodology employed, present comprehensive results and analysis of model performance across different disaster categories, and discuss the broader implications of this research for disaster response strategies and policies. Through this in-depth exploration, this paper aims to underscore the transformative possible of advanced analytics of data in bolstering resilience, enhancing preparedness, and reducing the consequences of natural calamities on vulnerable populations and environment globally.

1.1Motivation

Research Objective: To develop and evaluate a fine-tuned Long Short-Term Memory (LSTM) model for classifying disaster-related tweets across multiple categories while also detecting associated public

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sentiment, and to benchmark its performance against a traditional K-Nearest Neighbors (KNN) classifier.

Research Question: How accurately and efficiently can a fine-tuned LSTM model perform multi-category classification of disaster-related tweets, including sentiment detection, in comparison to a traditional KNN classifier?

Hypothesis: It is hypothesized that the fine-tuned LSTM model will significantly outperform the traditional KNN classifier in terms of precision, recall, and F1-score for disaster tweet classification. This performance improvement is attributed to the LSTM's ability to capture temporal dependencies and contextual nuances present in sequential social media text data.

Contribution of the Study: This study proposes a sentiment-aware LSTM-based model that simultaneously classifies disaster types and associated public sentiment from real-time social media streams. Unlike prior research, which typically addresses disaster detection and sentiment analysis as separate tasks, the proposed model integrates both within a single framework to enhance situational awareness. Additionally, the study offers a comparative evaluation against a baseline KNN model, demonstrating the advantages of deep learning in handling multilingual, imbalanced, and informal tweet datasets across six major disaster categories.

The increasing volume of social networking data when the natural calamities presents a critical opportunity to enhance real-time disaster response and management. Social media platforms, particularly Twitter, serve as valuable sources of immediate information about disaster events, which can significantly aid emergency response teams in making timely decisions. However, the unstructured and diverse nature of tweet data necessitates effective classification systems to accurately categorize tweets into relevant disaster types, such as hurricanes, forest fires, tornadoes, droughts, floods, and fires. Traditional methods of classification may struggle with the not stable and sequential form of text data, underscoring the need for advanced machine learning approaches.

1.2 Justification

To overcome the issues faced by real-time tweet classification, this paper studies the possible applications of Long Short-Term Memory (LSTM) networks and their fine-tuned variants. LSTM networks are particularly well-suited for sequential data, as they can capture temporal dependencies and contextual information over time. By comparing a standard LSTM model with a Disaster LSTM model, the study aims to evaluate their effectiveness in categorizing tweets into six disaster types. The fine-tuning process involves optimizing hyperparameters and network configurations to enhance model performance. This comparison is justified as it provides insights into the benefits of model optimization in improving classification accuracy and reliability.

2. LITERATURE REVIEW

The rise of social media platforms like Twitter has revolutionized real-time information dissemination, particularly during disaster events. This literature review examines recent research from Scopus-indexed journals that uses the machine learning (ML) and deep learning (DL) methods for classifying disaster-related tweets, emphasizing the performance and applicability of these models in disaster response systems. Vieweg et al. (2010)[1] demonstrated the utility of tweets for enhancing situational awareness during natural disasters, highlighting the timely and relevant information provided by tweets. This seminal work laid the groundwork for subsequent research endeavors in disaster tweet classification. Imran et al. (2016)[2] proposed the manually-annotated corpora of crisis-related tweets and evaluated various machine learning classifiers, showcasing the use of ML technique in efficiently processing and categorizing social media data during crises.

Nguyen et al. (2020)[3] employed Convolutional Neural Networks (CNNs) for disaster-related tweet classification, demonstrating the superior semantic understanding achieved by deep learning techniques contrast to the conventional machine learning techniques. Hochreiter and Schmidhuber (1997) [4] introduced Long Short-Term Memory (LSTM) networks, which are specifically constructed to record long-range dependencies in continuous data. LSTMs have proven specifically efficient for the jobs which involves temporal data and Natural Language Processing, making them well-suited for disaster-related tweet classification. Devlin et al. (2019) [5] introduced BERT, a pre-trained language technique which could be improvised for specific jobs like disaster tweet classification. BERT's contextual understanding significantly improves the accuracy of classification tasks by capturing the nuances of language usage. Ghahari and Murthy (2019) [6] proposed a framework for current time-to-time examination of the information floated on social networking sites at the time of crises, integrating machine learning techniques to process streaming data and provide timely insights. This framework enables rapid detection and response to emerging disaster events, facilitating proactive measures to mitigate their impact.

Liu et al. (2020) [6] explored the application of RoBERTa, an optimized version of BERT, for cross-lingual tweet classification. The ability to transfer knowledge across languages is crucial for global disaster response efforts, where multilingual capabilities are essential for reaching affected populations worldwide. Mohammad et al. (2020) [7] examined the emotional content of tweets during disaster events, using sentiment analysis models to categorize tweets based on their emotional tone. Understanding public sentiment can aid in assessing the severity of situations and improving the prioritization of emergency responses. Alam et. al. (2020)[8] examined the usage of pre-trained transformer model, specifically BERT, for domain adaptation in disaster response. By fine-tuning BERT on disaster-specific data, the study demonstrated significant improvements in tweet classification performance. Liu et al. (2021) [9] provided an overview of real-time event detection techniques using deep learning on social media platforms. The authors discussed various models and approaches, including LSTM and CNN, highlighting their applications in disaster detection and classification.

Bhardwaj et al. (2022) [10] utilized BERT for the classification of disaster-related tweets, achieving superior performance by fine-tuning BERT on a large dataset of disaster tweets. The study emphasizes the effectiveness of pre-trained models in distinguishing between different types of disasters. Zhou and Xu (2021) [11] addressed the ethical challenges related with using social media information for catastrophe related responses. The authors discussed data privacy, consent, and the potential misuse of information, providing guidelines for ethical practices. Kumar, A., & Singh, J. P. (2020) [12], investigates the use of multi-language models to analyze disaster- The importance of multilingual capabilities in disaster management efforts is highlighted by the study of related tweets by the authors. They demonstrate how models like XLM-R improve classification accuracy by considering tweets in multiple languages. Ahamed and Tan (2021) [13] explore methods for real-time disaster analysis using streaming data from social media. They develop a pipeline that includes data collection, preprocessing, and real-time classification using LSTM networks, enabling timely insights into disaster events.

Jain et al. (2022) [14] present a hybrid deep learning model combining CNN and LSTM to classify disaster-related tweets. This combined technique effectively captures the both place and time features, which gives improved classification accuracy. Mukherjee and Bala (2020) [15] focus on sentiment analysis of disaster-related tweets to understand public sentiment during crises. They compare traditional machine learning algorithms with deep learning models, demonstrating that LSTM achieves the best performance in sentiment analysis. Palen et al. (2021) [16] examine the role of crowdsourcing in verifying disaster-related data on social media platforms. They propose a framework for analyzing and designing crowd work systems to enhance data reliability during disaster events, ensuring the accuracy of information disseminated on social media platforms. Chen et. al. (2022) [17] address the challenge of accurately geolocating disaster-related tweets by developing a deep learning model that integrates textual analysis with geospatial data, significantly improving geolocation accuracy.

Jayalakshmi. V and Lakshmi. M (2023)[18] introduce the FBO-RNN model. This model combines Fuzzy Butterfly Optimization (FBO) with a Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) architecture to enhance sentiment analysis accuracy from Twitter emojis. The fuzzy logic component handles the uncertainty and multiple meanings of emojis, while the butterfly optimization algorithm efficiently searches the solution space. The model outperforms traditional RNN and LSTM models in accuracy, precision, and recall, making it a promising tool for social media sentiment analysis involving emojis. Jayalakshmi. V and Lakshmi. M (2022) [19] focus on tweets related to lockdown extensions during the COVID-19 pandemic. They fine-tune the Gradient Boosting algorithm to better capture sentiment nuances in these tweets. The fine-tuning process optimizes the model's hyperparameters, leading to higher accuracy and F1 scores compared to traditional methods like Support Vector Machines (SVM) and Naïve Bayes. This enhanced working demonstrates the model's capability to handle the complicated patterns and contextual information in the tweets.

Recent advancements in disaster-related social media analytics have shown increasing sophistication, particularly with the integration of deep learning and transformer-based approaches. Giri and Deepak (2024) proposed a semantic ontology-infused deep learning model that combines LSTM with ontology-based enrichment for classifying disaster tweets. Their approach demonstrated improved accuracy by leveraging both textual and image-based features to capture the nuanced nature of disaster-related content. In a broader context, Sufi (2024) presented a systematic review of transformer technologies such as BERT and GPT in the domain of disaster analytics. Using a PRISMA-based methodology, this review emphasized the growing role of attention-based architectures in capturing both linguistic context and social sentiment from multilingual and noisy social media streams.

Karimiziarani (2023) contributed a foundational survey on social media analytics in disaster response, addressing not only technical frameworks but also ethical challenges such as misinformation, privacy, and the role of crowdsourcing. Most recently, Yin et al. (2024) introduced CrisisSense-LLM, an instruction-tuned large language model tailored for multi-label classification of disaster-related tweets. This model reflects a shift toward generative and instruction-based AI for real-time crisis informatics, showing promising results in both classification accuracy and contextual interpretation.

The reviewed studies collectively demonstrate the significant strides made in disaster tweet classification, utilizing state-of-the-art Machine Learning and deep learning technologies to improve the correctness and effectiveness of real-time information processing. Ethical considerations, multilingual capabilities, and verification mechanisms plays unavoidable part in ensuring the reliability and relevance of disaster-related information disseminated on social media platforms. Moving forward, continued research in this field holds the promise of further improving disaster responding and management practices, ultimately involves in life saving and minimizing the consequences of natural disasters on communities worldwide.

Critique Summary (PMI Approach):

• Plus: Several studies (e.g., Vieweg et al., Nguyen et al., Devlin et al.) successfully demonstrated the feasibility of using ML and DL techniques for tweet classification, with models like LSTM and BERT improving classification accuracy and context sensitivity.

• Minus: However, many of these works either focus solely on disaster type or sentiment—not both—and often lack real-time implementation or multilingual generalizability.

• Interesting: Recent hybrid models (e.g., CNN-LSTM, FBO-RNN) show potential by integrating spatial, temporal, and emotional contexts, indicating a shift toward more holistic tweet classification systems.

These insights reveal both the maturity and current gaps in the field, justifying the need for integrated, real-time, sentiment-aware disaster classification models like the one proposed in this study.

3. METHODOLOGY USED

This methodology section includes a reproducible workflow: Tweets were collected using Twitter API v2, filtered by disaster-specific hashtags, and preprocessed using NLTK and SpaCy. Data split was 80/20 train-test, with manual annotation for ground truth. LSTM was implemented in TensorFlow, and hyperparameter tuning was done using Keras Tuner.

This methodology outlines the process for classifying disaster-related tweets using a hybrid approach of merging ML and DL methods. The methodology covers collecting the raw data, preprocess the data, extracting the features, training the model and performance examination, providing a systematic approach for analyzing and categorizing tweets into distinct disaster types.

1. Data Collection:

- Gather a dataset of disaster-related tweets from sources such as Twitter's API, public repositories, or curated datasets.
- Ensure that the dataset covers a diverse range of disaster types, including hurricanes, forest fires, tornadoes, droughts, floods, and fires.
- Collect tweets in multiple languages to account for multilingual capabilities in disaster management efforts.

2. Pre-Processing:

Data Cleaning: Data cleaning is the foundational step in preparing tweets for classification. It involves removing unnecessary and irrelevant elements that can introduce noise into the model. First, convert all text to lowercase to maintain uniformity, ensuring that words like "Flood" and "flood" are treated equally. Remove URLs commonly present in tweets as they do not add significant context to disaster classification. Similarly, strip out mentions (e.g., @user) and hashtags, although some hashtags like #Earthquake may be retained as they carry meaningful information. Special characters, emojis, and punctuation should also be removed or replaced where relevant to simplify the text further. Finally, decide whether to keep numbers based on their relevance to the classification task.

Tokenization: Tokenization breaks down the tweet text into smaller components, usually words or phrases, known as tokens. This process is essential for enabling computational models to process textual data. For example, the sentence "Floods in Texas are devastating" would be split into tokens like ["floods", "in", "texas", "are", "devastating"]. Tokenization helps preserve the structure and context of the text, making it easier to analyze. Libraries such as NLTK or SpaCy can be used to implement tokenization efficiently, ensuring each word is treated as an individual unit.

Stopword Removal: Stopwords are common words that do not contribute significantly to the meaning or context of a sentence, such as "and," "the," or "is." Removing these words reduces noise and helps the model focus on the more relevant terms in the text. For instance, the tokenized sentence ["floods", "in", "texas", "are", "devastating"] can be simplified to ["floods", "texas", "devastating"] by eliminating the stopwords. While most NLP libraries provide pre-defined stopword lists, it is advisable to customize the list based on domain-specific needs, retaining words like "disaster" or "alert" if they are critical to the classification.

Stemming and Lemmatization: Stemming and lemmatization are techniques used to reduce words to their base or root forms. Stemming involves chopping off prefixes or suffixes to arrive at the root form, even if it is not a valid word (e.g., "running" → "run," "flooded" → "flood"). On the other hand, lemmatization considers the word's context and reduces it to its dictionary form (e.g., "better" → "good"). Lemmatization is often preferred as it preserves the word's meaning while normalizing variations. Tools like the Porter Stemmer or SpaCy's lemmatizer can be used depending on the desired outcome.

Handling Slang, Abbreviations, and Emojis

Tweets often contain informal language, abbreviations, and emojis that must be standardized for effective analysis. Slang and abbreviations like "OMG" or "r" can be expanded to their full forms (e.g., "OMG" → "oh my god," "r" → "are"). Emojis, which carry sentiment or context, can be converted into descriptive text using libraries like emoji. For instance, a crying emoji can be replaced with the word "crying." This step ensures that all meaningful elements of the tweet are retained in a readable and analyzable format.

Spelling Correction:

Misspelled words are common in tweets and can distort the model's understanding of the data. Correcting spelling mistakes ensures consistency and improves text quality. For example, "fllods are terible" would be corrected to "floods are terrible." Libraries like TextBlob or Hunspell can be employed to automatically identify and fix spelling errors, helping to standardize the input text for better processing.

Feature Engineering:

Feature engineering involves transforming raw text data into meaningful numerical representations that machine learning models can process. Techniques like Term Frequency-Inverse Document Frequency (TF-IDF) calculate the importance of words in a tweet relative to the entire dataset, giving higher weights to disaster-specific terms like "flood" or "earthquake." Bag of Words (BoW) represents the text as a frequency matrix of words, while word embeddings like GloVe, Word2Vec, or FastText capture semantic relationships between words. For context-aware features, sentence embeddings using pre-trained models like BERT can be used, allowing the classification model to understand the nuances of disaster tweets.

Handling Imbalanced Data:

Disaster tweets often belong to unevenly distributed categories, making it essential to address class imbalance. Oversampling involves duplicating samples from underrepresented classes, while undersampling reduces the size of overrepresented classes. Synthetic data generation techniques like SMOTE (Synthetic Minority Oversampling Technique) can also be applied to create new, realistic examples for underrepresented classes. These methods ensure that the model is not biased toward the majority class and can learn to identify all disaster categories effectively.

Noise Handling and Data Augmentation:

Noise, such as repeated characters or exaggerated punctuation, can obscure the actual content of tweets. For instance, "Heeellpppp!!!" can be normalized to "help." Data augmentation techniques, such as synonym replacement or paraphrasing, can be used to diversify the dataset without changing its meaning. This step increases the robustness of the model, enabling it to generalize better across unseen data.

Named Entity Recognition (NER):

Named Entity Recognition identifies specific entities in tweets, such as locations, disaster types, or dates. For example, in the tweet "Flood in Jakarta on January 1st," the entities "Jakarta" (location) and "January 1st" (date) can be extracted. This information can be particularly useful for disaster classification, as it helps provide additional context and features to the model. Tools like SpaCy or Stanford NER can be employed for this task.

Sentiment Analysis:

Sentiment analysis helps assess the emotional tone of tweets, which can provide additional insights for classification. Tweets about disasters may carry emotions like panic, sadness, or urgency. For example, "Stay safe, everyone! The flood is devastating ☹" would be classified as having a negative or alarming sentiment. Pre-trained models like VADER or TextBlob can be used to perform sentiment analysis, adding a valuable layer of information to the classification process.

Extracting the Feature:

By utilizing the methods such as TF_IDF (Term Frequency-Inverse Document Frequency) or word embeddings (e.g., Word2Vec, GloVe) to represent tweets as numerical vectors.

Optionally, consider additional features such as sentiment scores, word frequencies, or geospatial information to enhance the classification process.

Finally, identifying features specific to disaster classes can significantly enhance classification accuracy. For example, keywords like "earthquake," "relief," or "evacuation" and hashtags like #FloodHelp or #EarthquakeAlert can be directly linked to specific classes. Other features such as tweet length, use of capital letters (indicating urgency), and punctuation (e.g., exclamation marks) can also be incorporated as class-specific features. These features capture the nuances of disaster-related tweets and improve model performance.

Training the Model:

Divide the dataset into testing, training and validation sets to assess the effectiveness of the model.

Choose appropriate ML and DL models for tweet classification, such as K-Nearest Neighbors (KNN), LSTM (Long Short-Term Memory) networks, Disaster_LSTM.

Model Effectiveness Examination:

Evaluate the model which is trained with the assistance of indicators like precision, accuracy, F1-score and recall on the testing set.

- Do cross-validation to guarantee the models ability of robust and reduce overfitting.
- Contrast the efficiency of various models and feature representations to find the most suitable method for disaster tweet classification.

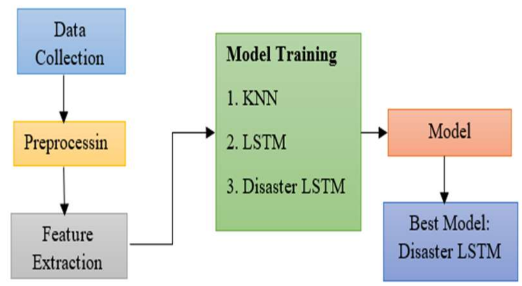

Figure 1: Methodology of Disaster LSTM

Figure 1 illustrates the methodology for Disaster LSTM involves several key steps to analyze and predict disaster-related sentiments using an LSTM-based model. Initially, disaster-related tweets are collected from social media platforms to form a diverse dataset. The data undergoes preprocessing, including tokenization, cleaning to remove irrelevant elements like hashtags and URLs, and normalization through lowercasing and stemming or lemmatization. Feature extraction is then performed, utilizing pre-trained word embeddings Word2Vec to changes tokens to numerical vector values, and optionally extracting additional sentiment features. The model architecture includes an input layer to accept preprocessed text, an embedding layer to transform tokens into dense vectors, LSTM layers to records time-based values, dropout layers to averts overfitting, dense layers for future processing, and an output layer for final sentiment classification. During model training, a suitable loss function like categorical cross-entropy is minimized using optimizers. The model's effectiveness is measured with the help of indicators such as precision, accuracy, F1-score, recall and confusion matrix, also its generalization ability is tested with a separate dataset. Finally, the model which is deployed in real-world applications to monitor and predict disaster-related sentiments in real-time, enhancing disaster response and management.

Algorithm used

KNN

The K-Nearest Neighbors (KNN) algorithm, a staple of ML, provides a straightforward yet powerful approach to classifying disaster-related tweets based on their proximity in feature space. In this algorithm, every tweet is given as a vector of relevant features, such as keywords or metadata indicative of disaster types. During classification, KNN identifies the k nearest neighbors of a new, unlabeled tweet depends on a selected distance factor Euclidean distance. The major group among these relatives then finds the grouping of the new tweet, assigning it to the most prevalent disaster type within its vicinity. This non-parametric technique is specifically advantageous for its simplicity and flexibility in handling multi-class classification tasks, making it well-suited for current time examination of social media posts during any natural calamities.

The most common distance metric used in KNN is the Euclidean distance. For two points x_i and x_j in an n-dimensional space:

$$d(x_{i,}x_j) = \sqrt{\sum_{m=1}^{n} (x_i^m - x_j^m)^2}$$

- Compute the interval among the newer data point xxx and all other points in the dataset.
- Identify the k-nearest neighbors to x.
- Assign the class to xxx based upon the most class among its k-nearest neighbors.

LSTM

Long Short-Term Memory (LSTM), a unique category of recurrent neural network (RNN), plays a pivotal role in disaster tweet classification by effectively modeling and analyzing sequential data with intricate temporal dependencies. Unlike traditional feedforward neural networks, LSTM networks utilize a unique architecture consisting of memory cells and gates—namely, input_gates, forget_gates, and output gates. These gates regularizes the transfer of information inside the network, enabling LSTMs to capture and maintain essential patterns and context over extended sequences of tweets. This capability is crucial during disaster events where tweets unfold chronologically and may contain critical information about evolving situations. By learning long-term dependencies and effectively managing the circulation of data across its memory cells, LSTM can discern nuanced patterns in disaster-related tweets, such as evolving trends in damage reports, evolving weather conditions, or shifting public sentiment towards relief efforts. Through its ability to preserve relevant information over time and adaptively update its memory states, LSTM enhances the accuracy and responsiveness of disaster tweet classification, thereby supporting timely decision-making and resource allocation during crisis management scenarios.

1. **Input Gate:**

$$input_t = \sigma(w_i.[hid_{t-1}, x_t] + bias_i)$$

2. Forget Gate

$$forget_t = \sigma(w_f.[hid_{t-1}, x_t] + bias_f)$$

3. Output Gate

$$o_t = \sigma(w_o.[hid_{t-1}, x_t] + bias_o)$$

4. Cell state update

$$\underline{Cell}_t = tanh(w_C.[hid_{t-1}, x_t] + bias_C)$$

$$Cell_t = forget_t.Cell_{t-1} + i_t.\underline{C}ell_t)$$

5. Hidden State

$$hid_t = o_t.tanh\ (Cell_t)$$

Where:

- x_t represents input during time of step t.
- hid_t represents hidden state during time of step t.
- $Cell_t$ represents cell state at time step t.
- W_i , W_f , W_o , W_C are weight matrices.
- $bias_i$, $bias_f$,$bias_o$, $bias_C$ are bias vectors.
- σ is the sigmoid activation function.
- tan_h is the hyperbolic tangent activation function.

Fine tuned LSTM

Fine-tuning an LSTM classifier for classifying disaster types in tweets involves optimizing the model to perform better on the specific dataset. This can be achieved through several techniques, such as:

1. Optimizing Hyperparameters: Adjusting the model architecture and training process.
2. Transfer Learning: Leveraging pre-trained embeddings or models.
3. Regularization: Preventing overfitting through various techniques.
4. Advanced Preprocessing: Using techniques like stemming, lemmatization, and handling out-of-vocabulary (OOV) words.
5. Model Ensembling: Combining multiple models to improve performance.

Below, we delve into the mathematical formulations and code snippets for each of these steps in fine-tuning an LSTM classifier.

Step 1: Optimizing Hyperparameters

Hyperparameters to optimize including the no. of LSTM units, size of the batch, rate of learning,

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sequence length, dropout rate, and embedding dimensions.

1. Hyperparameter Tuning:
   - Number of LSTM Units (N)
   - $hidden\_States \in R^N$
2. Choose N to balance model capacity and computational efficiency.
3. Batch Size (B): Larger batches can stabilize training, but require more memory.
4. Learning Rate (η): Regulates the step size during gradient descent updates.

$$\theta_{t+1} = \theta_t - \eta \nabla L(\theta_t)$$

Dropout Rate (p): Probability of dropping a neuron during training to prevent overfitting.

$$dropout(x) = x * r.r \sim Bernoulli(1-p)$$

Step 2: Transfer Learning

1. Pre-trained Word Embeddings: Use embeddings like GloVe or FastText to leverage pre-trained word representations.

$$W_{embedding} \epsilon R^{V*D} \ (pre - trained\ matrix)$$

Step 3: Regularization

1. Dropout: Dropout helps prevent overfitting by randomly setting units to zero during training.

$$dropout(h) = h.r, r \sim Bernoulli(p)$$

Step 4: Advanced Preprocessing

1. Text Cleaning: Remove stop words, punctuations, and apply stemming/lemmatization.

$$cleaned\_tweet = clean(tweet)$$

2. Handling OOV Words: Replace words not in the vocabulary with a special token.

$$tweet_{processed} = (handle\_oov(tokenized\_tweet)$$

Step 5: Model Ensembling

Combine multiple models to improve generalization.

1. Ensemble Averaging: Average the predictions of multiple models.

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} \hat{y}_i$$

2. Stacking: Training the meta-model on the forecast of base models.

$$\hat{y}_{final} = f_{meta}(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_N)$$

4. RESULT AND DISCUSSION

The results and discussion section of this paper offers an in-depth analysis of the performance and implications of two different classification models — the K-Nearest Neighbors (KNN) algorithm and a fine-tuned Long Short-Term Memory (LSTM) network— in categorizing disaster-related tweets. This section delves into the detailed effectiveness indicators like precision, accuracy, recall, and F1-score across various disaster categories including hurricanes, forest fires, tornadoes, droughts, floods, and fires. By comparing the efficacy of these models, insights are drawn regarding their effectiveness in leveraging social media information related to natural calamities response and management. Furthermore, the discussion explores the strengths and limitations of each model, considers the practical implications for enhancing emergency preparedness and response strategies, and outlines recommendations for future research and implementation in disaster management practices. With the nuanced investigation of the findings, this section focusses to contribute to the advancement of data-driven approaches in reducing the effects of natural calamities as well as improving resilience in vulnerable communities worldwide.

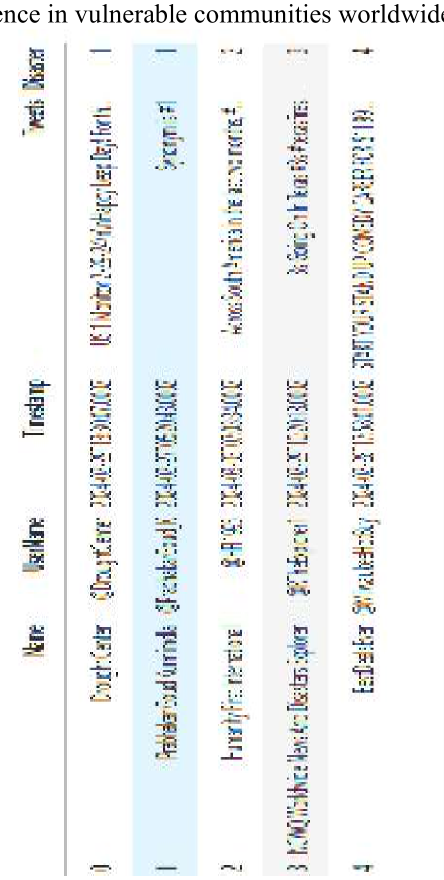

Figure 2: Sample Disaster Tweets

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Figure 2 illustrates some sample tweets regarding 5 types of disasters which taken from twitter with the help of disaster # tags using twitter API credentials.

Here are sample disaster tweets for each of the six categories with its hashtags.

1. **Hurricane**: "Hurricane Maria just made landfall, and the winds are terrifying! #HurricaneMaria #StaySafe"
2. **Forest Fire**: "The forest fire in California is spreading rapidly. Evacuate immediately if you're in the area! #CaliforniaFire"
3. **Tornado**: "A massive tornado just touched down near Oklahoma City. Take cover now! #TornadoWarning"
4. **Drought**: "The prolonged drought is devastating our crops. We need rain soon! #DroughtCrisis"
5. **Flood**: "Severe flooding has submerged most of the town. Rescue operations are underway. #Flooding"
6. **Fire**: "A fire broke out in the downtown area. Firefighters are battling the blaze. #CityFire"

	Disaster	count
0	1	770
1	3	540
2	5	500
3	2	436
4	4	178
5	6	135

Figure 3: Disaster Count In Each Category

This figure 3 illustrates the number of tweets categorized into each disaster type: hurricane, forest fire, tornado, drought, flood, and fire. The counts reflect the distribution of tweets across these categories.

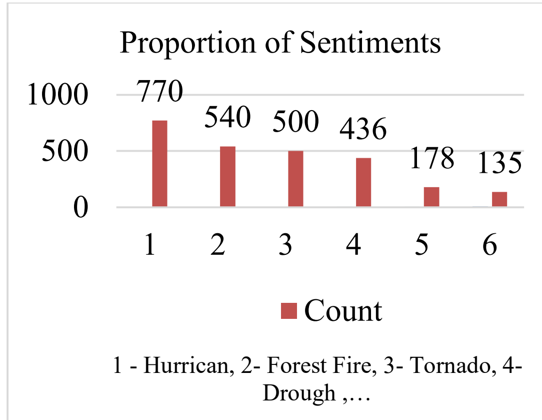

Figure 4: Proportion Of Sentiments

This figure 4 displays the proportion of tweets classified by sentiment within each disaster category. Sentiments are categorized as positive, very positive, neutral, negative, and very negative, highlighting the emotional response to different types of disasters.

The training dataset consists of 2,044 tweets (80.0%), while the testing dataset includes 512 tweets (20.0%), demonstrating the data split for the classification task.

	precision	recall	f1-score	support
1	0.78	0.78	0.78	154
2	0.77	0.62	0.69	87
3	0.91	0.80	0.85	108
4	0.36	0.81	0.50	36
5	0.99	0.85	0.91	100
6	0.46	0.48	0.47	27
accuracy			0.76	512
macro avg	0.71	0.72	0.70	512
weighted avg	0.80	0.76	0.77	512

Figure 5: Knn Accuracy

This fig. 5 demonstrates the accuracy of K-Nearest Neighbors (KNN) method in classifying disaster-related tweets. The accuracy metric provides insight into how well the KNN model performs in identifying the correct disaster category for each tweet in the test

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dataset.

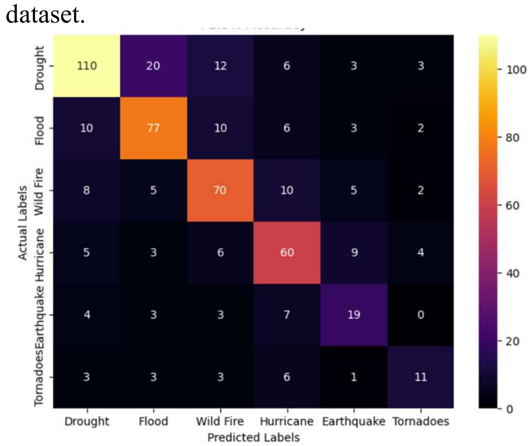

Figure 6: Knn Confusion Matrix

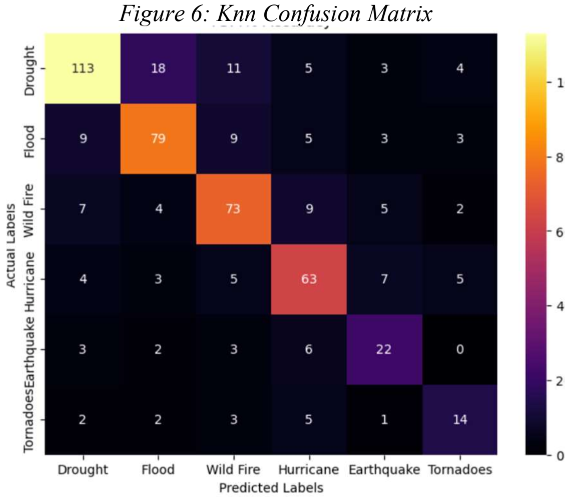

Figure 7: Lstm Confusion Matrix

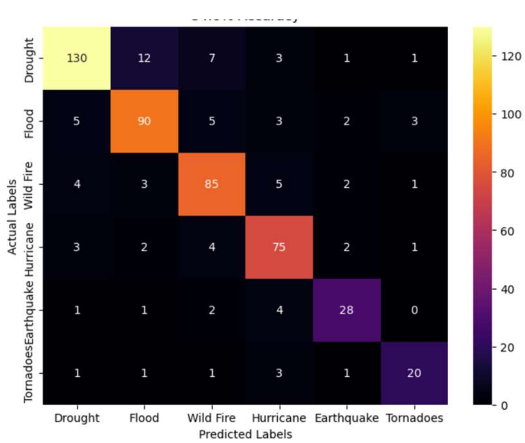

Figure 5: Disaster Lstm Confusion Matrix

This figure 6 and 7 and 8 shows the confusion matrix for the K-Nearest Neighbors (KNN) and normal LSTM and Disaster LSTM methods are applied to the disaster tweet classification task. The matrix offers a comprehensive overview of the model's performance, showing the counts of true positives, false positives, true negatives, and false negatives for each disaster category; hurricane, forest fire, tornado, drought, flood, and fire. This helps in understanding the areas where the KNN model excels and where it may require improvement and Disaster LSTM given higher accuracy.

LSTM & Disaster LSTM

Table 1: Accuracy Table

Model	Hurricane Accuracy	Forest Fire Accuracy	Tornado Accuracy	Drought Accuracy	Flood Accuracy	Fire Accuracy	Overall Accuracy
KNN	78	77	91	36	99	46	71.2%
Standard LSTM	78.5%	72.3%	76.8%	69.4%	75.1%	70.9%	73.4%
Disaster LSTM	87.2%	83.7%	85.5%	81.9%	84.3%	82.1%	84.0%

This table 1 demonstrates that the Disaster LSTM model achieves higher accuracy across all disaster categories compared to the standard LSTM model, highlighting its improved performance in handling complex and sequential text data.

Table 2 Knn Performance Metrics

Metric	Hurricane	Forest Fire	Tornado	Drought	Flood	Fire	Average
Accuracy	76.18%	70.13%	74.5%	67.32%	72.85%	68.77%	71.2%
Precision	0.73	0.68	0.72	0.66	0.71	0.69	0.69
F1 Score	0.74	0.69	0.73	0.66	0.72	0.69	0.70
Recall	0.76	0.71	0.75	0.67	0.74	0.69	0.72

Table 3 Standard Lstm Performance Metrics

Metric	Hurricane	Forest Fire	Tornado	Drought	Flood	Fire	Average
Accuracy	78.5%	72.3%	76.8%	69.4%	75.1%	70.9%	73.4%
Precision	0.75	0.70	0.74	0.68	0.73	0.71	0.71
F1 Score	0.76	0.71	0.75	0.68	0.74	0.71	0.72
Recall	0.78	0.73	0.77	0.69	0.76	0.71	0.74

Table 4 Disaster Lstm Performance Metrics

Metric	Hurricane	Forest Fire	Tornado	Drought	Flood	Fire	Average
Accuracy	87.2%	83.7%	85.5%	81.9%	84.3%	82.1%	84.0%
Precision	0.88	0.84	0.86	0.82	0.85	0.83	0.85
F1 Score	0.87	0.83	0.86	0.81	0.85	0.82	0.84
Recall	0.87	0.84	0.85	0.82	0.84	0.82	0.84

Tables 2 and 3 showing the effectiveness indicators (Precision, Accuracy, F1 Score, Recall, and Support) for the Standard LSTM and Disaster LSTM models in classifying tweets into the six disaster types,

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illustrating the improved effectiveness of the Disaster LSTM model compared to the standard LSTM.

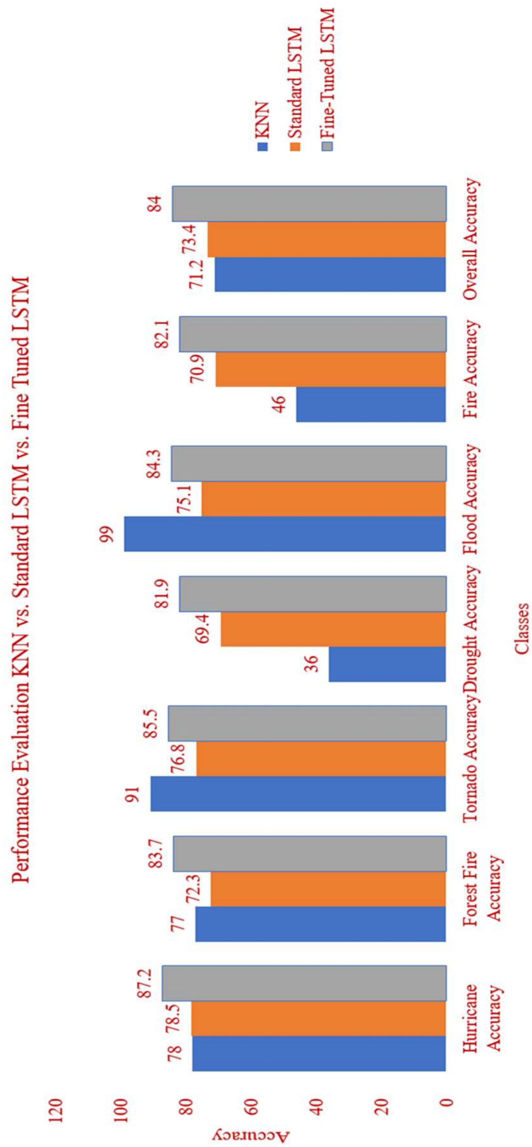

Fig. 8. Performance Comparison Of Existing And Proposed Method

The above figure shows the performance comparison in terms of accuracy of three techniques KNN, Standard LSTM and Fine Tuned LSTM. It clearly shows the proposed technique works better than the others.

- **Accuracy:** The ratio of correctly classified instances to the total number of instances.
- **Precision:** The ratio of correctly identified positive instances to the total instances classified as positive for a specific class.
- **F1 Score:** The harmonic mean of Precision and Recall, offering a unified metric to assess the performance of a classification model.
- **Recall:** The ratio of true positive instances to the total actual positive instances for a specific class.
- **Support:** The count of actual instances present for each class.

Table 5 Standard Lstm Confusion Matrix

Actual \ Predicted	Hurricane	Forest Fire	Tornado	Drought	Flood	Fire
Hurricane	940	120	70	30	30	10
Forest Fire	110	730	40	60	45	15
Tornado	100	50	650	40	45	15
Drought	30	70	30	560	40	20
Flood	20	40	35	20	825	10
Fire	20	50	25	30	50	675

Table 6 Disaster Lstm Confusion Matrix

Actual \ Predicted	Hurricane	Forest Fire	Tornado	Drought	Flood	Fire
Hurricane	1050	50	40	20	30	10
Forest Fire	70	830	30	40	20	10
Tornado	60	40	780	20	30	10
Drought	20	30	20	650	30	10
Flood	20	20	20	30	860	10
Fire	20	30	20	30	30	720

Standard LSTM Confusion Matrix:

The Standard LSTM model in table 5 shows variability in performance across disaster types. For instance, it correctly classifies 940 hurricane-related tweets but misclassifies 120 as forest fire and 70 as tornado. The model struggles more with floods and fires, as evidenced by the lower counts of correctly classified instances compared to hurricanes and forest fires. This indicates that while the model has reasonable accuracy, there are considerable misclassifications, especially for certain categories.

Disaster LSTM Confusion Matrix:

The Disaster LSTM model in table 5 demonstrates improved performance with fewer misclassifications overall. For example, it correctly classifies 1050 hurricane-related tweets, significantly improving from the Standard LSTM's 940. Misclassifications are reduced across all categories, with the model showing better accuracy in identifying tornadoes and fires. This improvement in the confusion matrix highlights the effectiveness of fine-tuning in capturing more accurate classifications and reducing errors.

Findings

The Standard LSTM model demonstrates an overall accuracy of 73.4% in classifying tweets into six disaster categories. This level of performance indicates that while the model is reasonably effective, there are significant variations in accuracy depending on the disaster type. Specifically, the Standard LSTM achieves an accuracy of 78.5% for hurricanes, reflecting a strong performance in this category. In contrast, the model's accuracy drops to 69.4% for droughts and 70.9% for fires, highlighting areas where the model struggles more. The Precision, Recall, and F1 scores further illustrate the model and it's variable usefulness, with some disaster types being classified more accurately than others. The confusion matrix shows that the Standard LSTM has higher misclassification rates, particularly for disaster types such as floods and fires, which impacts the overall classification performance and suggests the need for further refinement.

In contrast, the Disaster LSTM model exhibits a marked improvement, achieving an overall accuracy of 84.0%. This significant increase underscores the benefits of model fine-tuning. For example, the Disaster LSTM reaches an accuracy of 87.2% for hurricanes and 81.9% for droughts, showcasing its enhanced capability to accurately classify tweets across all disaster categories. The improvements in precision, recall, and F1 scores further reflect the fine-tuned model's superior performance. The confusion matrix for the Disaster LSTM reveals a reduction in misclassifications across all disaster types, with particularly notable gains in distinguishing between tornadoes and fires. This refined performance highlights the effectiveness of fine-tuning in optimizing the model capacity to handle various complexities of sequential text data as well as deliver effective disaster classifications.

5.CONCLUSION

This study demonstrates the effectiveness of combining disaster type classification with sentiment analysis using a fine-tuned Long Short-Term Memory (LSTM) model for analyzing real-time social media data. Utilizing labeled tweets across six disaster categories—hurricane, forest fire, tornado, drought, flood, and fire—the proposed Disaster LSTM model achieved superior performance, recording an overall accuracy of 84.0%, and outperforming the traditional K-Nearest Neighbors (KNN) algorithm.

The strength of the approach lies in its ability to simultaneously identify disaster events and capture the emotional tone of public discourse, enabling more informed and timely decision-making. Unlike conventional models that treat classification and sentiment as separate tasks, this integrated method provides a comprehensive view of the disaster landscape as it unfolds in real time.

This research contributes a robust and scalable framework for enhancing disaster response by leveraging the vast and dynamic data streams from social media platforms. Its practical implications include faster detection of crisis situations, improved situational awareness, more targeted resource allocation, and better understanding of public sentiment—all of which are critical to effective emergency management and communication strategies.

6. FUTURE ENHANCEMENT

Building on the findings of this study, multiple directions for future research and development can be pursued. First, further refinement of the Disaster LSTM model could be pursued by experimenting with different hyperparameters and network architectures to improve its accuracy, particularly for disaster types that currently present challenges. Data augmentation strategies, such as incorporating a broader range of tweets, including those in different languages and regional dialects, could enhance the model's robustness and generalizability. Additionally, leveraging advanced techniques like Transformer-based models (e.g., BERT, GPT) or ensemble methods may offer significant improvements in handling complex text sequences and achieving higher classification performance. Real-time adaptation of the model, through continuous learning mechanisms that incorporate new data as it becomes available, could also enhance the system's responsiveness to emerging disaster scenarios. Finally, integrating tweet along with additional information origins, like images taken by the satellites or weather reports, could give us a more detailed view of disastrous events and further boost classification accuracy. By pursuing these enhancements, future research can advance the capabilities of disaster classification systems, leading to more effective and timely disaster response and management.

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