SP25: DATA-266 Sec 11 - Generative Model

Leveraging Large Language Models for Crisis Detection and Response

Instructor:

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Introduction:

The LLM-Supported Crisis Management System utilizes Large Language Models (LLMs) to improve wildfire response and emergency decision-making. The system handles real-time crisis information for precise, prompt, and organized reporting. The goal of this project is to enhance situational awareness, response effectiveness, and information precision for emergency teams managing wildfire events.

Datasets:

The *California Fire Incident* dataset provides information on historical wildfire incidents. It contains close to 40 attributes, including fire size, affected regions, firefighting efforts, and casualties. This dataset is useful for analyzing fire trends, predicting high-risk zones, and assessing fire suppression effectiveness. The second dataset we are planning to use is the *Wildfire Damage* dataset. It has 11 attributes including but not limited to incident date, location, area, homes burned etc. It gives information on wildfire events, highlighting the levels of devastation levels. This dataset plays an important role in estimating how the wildfires can affect communities, businesses, and infrastructure, which is essential for planning emergency responses and managing risks. Lastly, the *CrisisMMD Twitter-Based Wildfire* Dataset comprises social media posts (tweets) concerning wildfires, featuring text descriptions, images, metadata, and classifications labeled by humans. This dataset serves as a valuable resource for crisis detection, monitoring of social media, and analyzing public sentiment during wildfire events.

Project Summary:

Objective: The aim of our project is to create an AI-based crisis management system that employs Large Language Models (LLMs) to improve the detection of wildfires, evaluate their impact, and coordinate emergency responses. By utilizing structured datasets (historical data on wildfires), unstructured data from social media (crisis posts from Twitter), and AI-driven classification models, the system will deliver prompt alerts, condense emergency situations, and support responders in making crisis-related decisions.

Problem Statement: In January 2025, catastrophic wildfires struck Los Angeles, particularly the Palisades and Eaton Canyon fires. These incidents destroyed more than 9,400 buildings and necessitated the evacuation of over 30,000 residents. Conventional emergency response systems face challenges in processing vast amounts of data from various sources, which can result in delayed decision-making. Moreover, public posts on social media can provide critical information during a crisis, but extracting relevant and accurate insights from such unstructured data remains a significant challenge. This project addresses these challenges by integrating LLMs with wildfire incident datasets and social media crisis monitoring to improve situational awareness, emergency preparedness, and decision support during wildfires.

Proposed Approach & Novelty: To enhance wildfire response, this research suggests an AI-driven crisis management framework that combines social media insights, historical wildfire data, and Large Language Models (LLMs). To find trends and evaluate wildfire hazards, the method analyzes structured datasets like California Fire Incidents and Wildfire Damage. The CrisisMMD Twitter dataset will also be used to perform real-time crisis detection. Emergency responders will receive precise, real-time scenario reports instead of generic AI-generated responses because of the use of retrieval-augmented generation (RAG) and LLM-powered crisis summarization.

This initiative presents a flexible, AI-powered method that can adjust to changing wildfire circumstances. Utilizing social media crisis tracking, AI-based categorization, and automated emergency reporting offers a more efficient and scalable approach to disaster management.

Expected Impact & Contributions: This project will improve wildfire response effectiveness by utilizing LLMs to analyze crisis information from social media and official wildfire reports, facilitating quicker detection of urgent incidents. Moreover, the system will enhance situational awareness by categorizing wildfire-related social media posts into classifications like damage updates, impacted individuals, and emergency notifications. This will assist authorities in prioritizing response actions and distributing resources more efficiently.

Project Background:

Recent **advancements** in Large Language Models (LLMs) offer promising avenues to enhance crisis management through improved data analysis, decision support, and communication strategies. Current developments in LLMs have greatly improved crisis management abilities. Researchers have created models such as *CrisisSense-LLM*, specifically refined for multi-class classification of disaster-focused social media posts, increasing situational awareness in times of crisis. Moreover, the combination of LLMs with *Knowledge Graphs* has been proven to bolster emergency decision-making through context-rich, evidence-based insights.

Present LLM-supported crisis management systems encounter **challenges** in real-time data incorporation, domain-specific precision, and filtering misinformation. Numerous models have difficulty handling wildfire updates from various sources such as social media, emergency reports, and satellite data, resulting in delayed or incorrect crisis responses. Moreover, insufficient fine-tuning leads to standardized outputs that do not correspond with emergency protocols, and biases as well as misinformation present dangers in critical scenarios.

To improve the efficiency of LLM-Assisted Crisis Management, 4 **prompt engineering** methods will be utilized. *Chain-of-Thought (CoT) Prompting* enhances structured reasoning by deconstructing crisis information into distinct steps, enabling the LLM to produce emergency summaries. *Self-Consistency Decoding* will guarantee that the model creates trustworthy crisis alerts by producing various response options. *In-Context Learning (ICL)* allows the model to adjust to various wildfire situations by utilizing previous occurrences, enhancing precision in forecasting fire expansion and control methods. Lastly, *Role-based Prompting* will improve response accuracy by enabling the LLM to serve as a virtual emergency aide. This project also utilizes LLM strategies to tackle the obstacles by incorporating **Retrieval-based Augmentation**(RAG). **Fine-tuning** techniques such as *Reinforcement Learning from Human Feedback (RLHF)* ensures that the LLM produces correct, ethical, and crisis-suitable replies by training it on human-validated wildfire reports and emergency guidelines. *Parameter-Efficient Fine-Tuning (PEFT)* enables the model to swiftly adjust to wildfire-related terminology and immediate crisis information while reducing computational expenses, making it applicable for use in emergency response frameworks.

Literature Review:

Recent advancements in LLM-Assisted Crisis Management have explored multiple applications, including real-time emergency response and disaster information processing. Hakan T. Otal and M. Abdullah Canbaz (2024) proposed an LLM-based platform, LLAMA2, to classify and extract emergency information from social media for enhanced crisis coordination [1]. Research on CrisisSense-LLM by Kai Yin et al. (2024) has demonstrated the effectiveness of instruction-tuned models in multi-label classification of disaster-related tweets, improving situational awareness for emergency responders [2]. Additionally, Douglass et al. (2024) examined how LLMs can analyze crisis escalation patterns in international relations, providing valuable insights into event dynamics [3]. AI-driven systems like CReMa, developed by Lamsal et al. (2024), enhance cross-lingual crisis communication by integrating spatial, textual, and temporal data [4]. Moreover, DisasterResponseGPT, as discussed by Goecks et all. (2023), leverages prompt engineering to generate actionable response plans during emergencies, improving adaptability in crisis scenarios [5]. Weakly-supervised methods have also been applied to fine-grained event recognition, aiding disaster management efforts through enhanced categorization of crisis-related social media content, as explored by Yao et al. (2023) [6] . Evaluations of LLM-based triage systems, comparing ChatGPT and

Copilot Pro with human triage nurses, have shown the potential of AI in assisting emergency medical responses, as highlighted by Arslan et al. (2024) [7] . Additionally, research by Chakravarty et al. (2024) underscores how AI-enhanced early warning systems can improve disaster preparedness and crisis communication [8] . A paper by Faiaz et al. talks about a system that ensures real-time information and geographically relevant readiness is done to the needs of populations [9] . The use of AI for emergency vehicle coordination, explored by Peelam et al. (2024), has shown potential in optimizing response times and traffic routing during crisis situations [10]. Lei et al. (2025) presents a thorough survey of current LLMs in natural disaster management,and categorizes them based on disaster and application phases[11] . Furthermore, Li et al. (2024) did a study to get the accuracy and completeness of answers returned by ChatGPT when people need information about protective actions [12] . These advancements highlight the increasing role of LLMs in real-time disaster response, offering solutions for data-driven decision-making, situational awareness, and emergency communication. Rafi et al. (2024) discusses LLMs to address crisis-related challenges by dealing with incomplete speech, contextual gaps, and prioritizing calls based on severity [13]. Chen et al. (2024) has developed a system called Enhancing Emergency decision-making with Knowledge Graph and LLM (E-KELL), which helps in decision-making in various emergency stages [14] . The work by Lankford et al. (2024) discuss LLMs and MLLMs to improve MT capabilities [15].

Performance Evaluation:

The evaluation of the LLM-Assisted Crisis Management System will utilize various metrics to guarantee accuracy, relevance, coherence, and efficiency. We are considering using *BLEU* (Bilingual Evaluation Understudy) to assess the quality of crisis summaries by contrasting them with human-authored emergency reports, *FID* (Fréchet Inception Distance) to evaluate the semantic relevance of answers, guaranteeing factual correctness and reducing misinformation, accuracy for crisis classification tasks to assess how effectively the model classifies alerts associated with wildfires, whereas *F1-score* to guarantee both high precision and recall in identifying pertinent crisis information. Moreover, *response latency* (inference time) will be tracked to guarantee that alerts are produced effectively. The model's effectiveness will be evaluated against current benchmarks, such as human-generated emergency reports, standard rule-based classification systems, and general-purpose LLMs that have not undergone fine-tuning. Anticipated baseline metrics consist of a BLEU score of at least 0.6, FID score of no more than 10, accuracy of at least 85%, F1-score of at least 0.8, perplexity of 30 or lower, and a response latency of no more than 2 seconds for each query.

Work Division & Timeline:

Milestone	Task Description	Responsible Member(s)	Deadline
Milestone 1 (Weeks 1)	Data collection Preprocessing	Sugandha Hamsalakshmi	Feb 13, 2025 Feb 17, 2025
Milestone 2 (Weeks 2-6)	Implement & test 4 prompting techniques	Hamsalakshmi (2 prompting techniques) Sugandha (other 2)	Feb 20 to April 7, 2025
Milestone 3 (Week 7)	Progress Presentation 1	Both	April 9, 2025
Milestone 4 (Weeks 8-12)	Implement Fine-Tuning RAG Evaluation metrics Progress Presentation 2 Report	Hamsalakshmi Sugandha Sugandha Both Both	April 10 to May 2, 2025 April 23, 2025 April 30,2025
Milestone 5 (Week 13)	Final project presentation	Both	May 7, 2025