Short Paper: AI-Driven Disaster Warning System: Integrating Predictive Data with LLM for Contextualized Guideline Generation

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Short Paper: AI-Driven Disaster Warning System: Integrating Predictive Data with LLM for Contextualized Guideline Generation

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Abstract

Early warning systems are the backbone of disaster management, but traditional systems often send static alerts with no personalized advice. This work investigates an AI-powered disaster warning system using predictive analytics and LLMs to design personalized recommendations over efficient response strategies. This system ensures that real-time information on context-specific and geographically relevant preparedness is tailored to the needs of varied populations. It was built using the LangChain framework and features an architectural composition with a predictive layer in disaster monitoring and an advisory layer for proactive safety guidelines. It integrates current weather conditions with advanced machine learning algorithms to enhance disaster prediction and utilizes LLMs in constructing customized actions, hence streamlining emergency messaging with enhanced clarity and relevance. Among the tested models, it turned out that the Gemini Pro LLM is the most effective, consistently generating outputs appropriate in context and accurate. Analysis under different temperature settings demonstrated the ability of the model to maintain high precision on various types of crises. The findings indicate that this approach can transform traditional early warning systems into more adaptive, user-centered frameworks, hence enhancing disaster management practices.

CCS Concepts

• **Computing methodologies** → Artificial intelligence; Natural language processing; Natural language generation; • **Applied computing** → Operations research; Decision analysis; Multi-criterion optimization and decision-making; • **Computer systems organization** → Real-time systems; Real-time system architecture.

Keywords

AI-Driven Disaster Management, Early Warning Systems, Large Language Models, LangChain, Generative Analytics, Predictive Data Integration, RAG, Personalized Safety guidelines

*Place the footnote text for the author (if applicable) here.

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1 Introduction

Disaster preparedness may be defined as a systematic process that intrinsically integrates Early Warning System (EWS) into disaster management frameworks [1]. While the detection methods are important, effective public awareness of disaster threats is core to risk reduction [2]. Timely warnings allow the community to evacuate and take protective actions, thus reducing casualties and damages [3]. Traditionally, mass media is one of the most utilized methods for spreading disaster warnings, which would include radio and television broadcasts. In Bangladesh, government warnings are issued days before a cyclone's landfall via such mediums [4]. However, one very crucial factor in successful dissemination is community engagement. For instance, The Cyclone Preparedness Programme (CPP) in Bangladesh employs local volunteers to disseminate warnings and assist in evacuations [5]. Regardless of these strategies, present dissemination methods have considerable limitations. Information overload, conflicting messages, and technical jargon can cause confusion, delaying decision-making and reducing responsiveness to warnings [6, 7]. A study reveals that while radio and television had played a vital role in broadcasting crisis warnings, the messages often lack context and clarity, affecting community responses [8]. These limitations highlight the need for ancillary means of information provision. Recent advancements in disaster prediction are largely propelled by Artificial Intelligence (AI) and Machine Learning (ML). Studies reveal that AI analyzes historical and environmental data to enhance EWSs, supporting proactive disaster management [9, 10]. Verily, AI has been recognized as a revolutionary tool for environmental monitoring, opening the door to more accurate predictions and prompt responses [11]. ML algorithms use meteorological data to predict cyclone tracks, enhancing prediction accuracy [12]. This predictability aids early evacuations and resource allocation, saving lives and reducing economic losses [13]. While the prediction and monitoring have improved, the personalized warnings remain largely ignored. Generally speaking, early warning systems issue blanket warnings that cannot take into consideration the multitude of situations or needs of each community. AI can improve warning dissemination based on demographic data, but there is a significant lack of frameworks that take into consideration the customization of communications for individual vulnerabilities and levels of preparedness [1]. This disparity points out the need for further research and adaptive disaster warning systems to communicate hazards and instructions to different populations.

To address these gaps, we propose a holistic system using LangChain with Large Language Models (LLMs) to develop disaster protocols based on user geography, infrastructure, and characteristics of the disaster. An LLM is a distinct class of deep learning geared for the processing and creation of human language. These systems detect clear, situational recommendations with the aid of AI in data analytics and natural language processing to enable better responses to emergencies [14]. LangChain enhances LLMs by providing organized, relevant data to reduce incorrect or irrelevant responses [15].

The objectives of the proposed study may be summarized as follows:

1. Activate disaster warning mechanisms using artificial intelligence by integrating predictive data into large language models (LLMs), enabling the generation of tailored, context-specific instructional materials for disaster response.
2. Improve the efficiency of EWSs by applying LangChain with a view to improving LLM performance by enhancing precision, reducing the number of errors, and accounting for user-specific factors such as geography, infrastructure, and disaster characteristics.

2 Relevant Works

LLMs are promising tools in disaster management, harnessed to advance various response efforts. One of the key areas of exploration has been the application of LLMs in drafting disaster response plans. Goecks and Waytowich [16] demonstrated that LLMs can rapidly produce detailed action plans in scope and scale, similar to those developed by human experts, to dramatically accelerate the decision cycle. Building on this, Colverd et al. [17] and Chandra and Chakraborty [18] demonstrated practical uses of LLMs in flood and radiation emergencies. Apart from action plan generation, LLMs have also been applied to the identification and classification of emergency situations derived from social media. Otal et al. [19] proposed a novel use for LLaMA2 to help telecommunicators analyze 911 calls and provide instructions. Similarly, Yin et al. [20] developed an LLM for classifying disaster-related tweets to enhance real-time situational awareness. More recently, however, attention has shifted to the development of special-purpose LLMs to suit the particular disaster situation at hand. Li et al. [21] introduced "Havior", a visual analytics system powered by LLMs for heat risk management, whereas Wang et al. [37] proposed TyphoonT5, a question-and-answer system about typhoon disaster knowledge. In addition, Xie et al. [22] developed WildfireGPT, an LLM specialized in providing information related to the risks of wildfires. In addition, LLMs offer incredible prospects in agriculture, one of the leading sectors for climate change adaptation. Nguyen et al. [23] presented a prototype, 'My Climate Advisor', combining an LLM with retrieval-augmented generation to provide climate adaptation info to farmers.

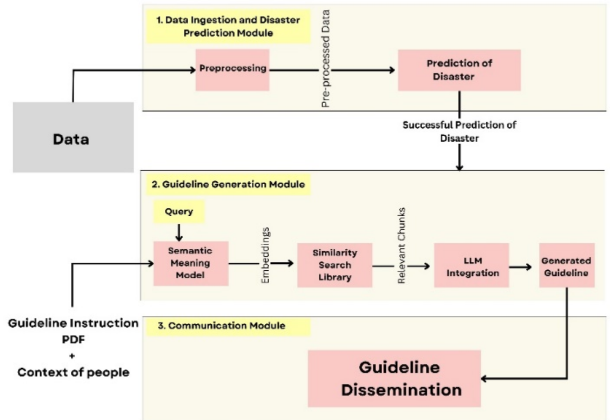

Figure 1: System workflow. This figure illustrates the key components of the core system.

These studies together indicate considerable potentials of LLMs toward improved disaster management via better decision-making, real-time analysis, and effective communication. However, speaking about their promising applications, Akter and Wamba [24] point out that there exist obstacles concerning the scarcity, unreliability, and inconsistency of data affecting the implementation of LLMs in disaster risk management. Overcoming such limitations is absolutely necessary to realize all possibilities of LLMs. Therefore, the goal of this research is to bridge this gap by proposing an AI-driven disaster warning system that incorporates predictive data along with LLMs for contextualized guidelines that ensure more accurate and personalized responses in critical situations.

3 System Architecture

The proposed architecture consists of two major layers: a predictive layer, which focuses on disaster surveillance, and an advisory layer that generates context-sensitive safety recommendations. The architecture essentially consists of three major components: (1) Data Ingestion and Cyclone Prediction Module, (2) Guideline Generation Module, and (3) Communication Module.

First, forecasts and predictions are collected from existing ML models or numerical algorithms that process real-time meteorological data to predict the exact time of occurrence, severity, and path of potential disasters. In this module, the LLMs dynamically generate personalized action plans by incorporating the predictions from the ML models along with information from a central database. Ultimately, the system ensures that these guidelines are disseminated promptly through SMS or email so that vital information reaches people in vulnerable situations on time.

4 Disaster Prediction

The traditional techniques integrated with the state-of-the-art methodologies of ML and deep learning have enhanced the disaster forecast by remarkably increasing the accuracy and speed of various types of natural hazard forecasts such as cyclones, floods, and landslides. For cyclones, deep learning models like CNNs, LSTMs, and hybrids achieve prediction accuracies up to 99.4% [25, 26]. ML methods like Gradient Boosting and SVM enhance cyclone tracking accuracy to 86–95% [27, 28]. Meanwhile, satellite imagery combined with GANs significantly enhances these feature extraction processes and predictive analytics [27]. Approaches such as SVR contributes to flood prediction accuracy up to 97.7% [29]. New methods, such as HD-TGCN, capture complex spatiotemporal relationships for enhanced prediction [30], while a number of ML/traditional hydrological models, including HEC-RAS, now offer daily predictions of flood extent [31]. Voting classifiers combining Random Forest and Gradient Boosting have further increased accuracy to nearly 99% [32]. Similarly, landslide forecasting has improved by incorporating the use of Physics-Informed Neural Networks (PINNs) [33]. ML and physical models accurately forecast landslide deformation stages, and temporal clustering enhances landslide susceptibility assessment [34],[35]. In summary, the progress made in predicting cyclones, floods, and landslides underscores the importance of amalgamating various methodologies for better disaster management [36]. These predictive models greatly enhance the precision and timeliness of disaster predictions while providing the necessary input for LLMs.

5 LLM-LangChain Based Guideline Generation

Our system uses the LangChain framework in conjunction with LLMs to dynamically produce context-specific safety rules for disaster preparedness. This section describes the methodology used; and how LLM-generated guidelines are integrated with disaster prediction models.

5.1 Methodology for Generating Context-Specific Guidelines

5.1.1 Data Ingestion and Preprocessing. The system is initiated by the ingestion of textual data derived from authoritative sources concerning disaster safety, including official guidelines and emergency response manuals. In this implementation, a PDF document (guideline.pdf) is employed as the primary data source. Before the text extraction, preprocessing of the documents was performed to standardize the format, ensuring consistency in text structure across multiple sources. The process of text extraction is represented as follows:

Extracted_Text=f(PDF_Document)

The text extraction function, represented by the letter f in this case, has been developed using the PyPDF2 package. This feature guarantees the thorough extraction of the recommendations from guideline.pdf while preserving the original content's scope and integrity.

5.1.2 Text Chunking and Embedding. RecursiveCharacterTextSplitter is used to segment the document into contextually cohesive segments to enable the handling of large volumes of textual information. Subsequently, the Google Generative AI model ingests these segments into high-dimensional vector representations. Here is a representation of the embedding function:

Vector=g(Text_Chunk)

where g is the embedding function. Indexing these vectors with FAISS (Facebook AI Similarity Search) makes it possible to carry

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Instructions:
You are a knowledgeable assistant focused on
providing safety guidelines for areas at risk of
disasters, such as cyclones. Your goal is to
generate personalized, clear, and actionable advice
based on the specific details provided about the
user's infrastructure, user's location, proximity
to the disaster pathway, Cyclone speed and distance
to the nearest shelter.

Please:
- Carefully analyze the provided context from the
PDF.
- Offer tailored guidance that addresses the user's
unique situation.
- Ensure that your advice is practical and directly
applicable.
- If information is missing or unclear, use logical
assumptions based on the context to provide the
best possible recommendations.
- Be concise but thorough, offering detailed steps
when necessary to enhance safety and preparedness.

Context:\n{context}\n
Question: \n{question}\n
Personalized Guideline:
```

Figure 2: An Example of a Prompt Template

out similarity searches efficiently. It is guaranteed to find the best recommendations that match the inserted input best. Cosine similarity has been used to figure out the proximity between two vectors. Prompt Design and LLM Integration.

A custom prompt template is designed to guide the LLM in producing just about accurate and relevant guidelines. The specific guidance in this template is carefully engineered to provide customized guideline that would consider the user's context, infrastructure, proximity to the disaster pathway, proximity to the nearest shelter, and other relevant information.

The LLM used in this system is the ChatGoogleGenerativeAI, and it has been parameterized on a conservative temperature of 0.3, thus ensuring that the generated output is creative enough but firmly based on the factual context taken out of the integrated text. The LangChain framework therefore supports an interaction among the user's question, vectorized segments of text, and a large language model into producing a response particularly relevant to the user's circumstance.

5.1.3 Integration with Predicted Disaster Track. Real-time forecasting of disaster trajectories can enhance the effectiveness of the established guidelines considerably. For example, in cyclones, deep learning models consider historical data and infrared images to provide predictive track information, which is vital for creating current guidelines.

This integration will make the system update guidelines adaptively with the change in the prevailing circumstance of the disaster context. Once the expected track of a cyclone or any such disaster changes, the LLM revises its suggestions by shifting its emphasis on newly at-risk areas and lowering attention to regions where the risk

Table 1: Summary of the Parameters Used:

Parameter	Value
Text splitter type	RecursiveCharacterTextSplitter
Chat model	ChatGoogleGenerativeAI
ChatOpenAI model name	"gemini-pro"
Vector store	FAISS
Embeddings type	GoogleGenerativeAIEmbeddings
Embeddings model name	"models/embedding-001"
Chunk size	10,000 characters with 1,000 character overlap
LLM temperature	0.3 (to ensure factual, creative responses)

has decreased. The guidance will remain relevant and applicable through such continuous adaptation.

6 Test and Evaluation

6.1 Guideline Generation and Scenario-based Evaluation

The LLM-LangChain-based system has significantly improved personalized safety recommendations for cyclone events. During the testing phase, the system effectively produced distinct guidelines tailored to a range of input Scenarios:

These two scenarios present opposite situations to evaluate the system's ability to generate accurate, context-sensitive recommendations. This effectively demonstrates the system's dynamic approach in providing real-time, context-sensitive guidance, contrasting with traditional static warnings.

To further assess the efficacy of different language models in generating personalized safety guidelines, we tested several other LLMs using the same input scenario-1 For instance, the Mistral-7B-Instruct-v0.1 model has given the following output to scenario-1:

6.2 Model Performance Comparison

To systematically compare the models on their effectiveness, we made an assessment based on the following criteria: guideline accuracy, relevance, clarity, language simplicity, logical flow, completeness, conciseness, and resource utilization. The evaluation results are displayed through bar charts (Figure 4) for each criterion for the comparison of the models' performances. The results indicate that Gemini-Pro outperformed the other models based on the provided evaluation criteria. Mistral-7B-Instruct-v0.1 showed a moderate level of performance; it demonstrated weaknesses in guideline accuracy and relevance. Also, it incorrectly assessed the level of risk and determined an incorrect nearest shelter location. However, it did provide guidelines that were fairly clear, logically arranged, and expressed in simple terms. On the other hand, HuggingFaceH4/zephyr-7b-beta also had a moderate performance; the model struggled with issues concerning accuracy and completeness. The instructions lacked clear action items to be undertaken, and there were inconsistencies concerning shelter. Both Tiiuae/falcon-7b and Google/flan-t5-base had unacceptable

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Based on the provided context, the user's location
falls under the Moderate Risk Area for Cyclone,
with a Cyclone Speed of 70 knots. The user's
infrastructure is classified as Weak, which
requires immediate evacuation, regardless of
Cyclone Speed. The nearest shelter is located at
(21.8824° N, 89.1824° E), which is approximately 15
kilometers away from the user's location. The user
should pack essential items, such as food, water,
and medication, and follow the evacuation route
provided by local authorities. It is recommended to
avoid traveling during the storm and to seek
shelter in a sturdy building or underground shelter
if possible. The user should also stay informed
about the storm's progress and follow any updates
or advisories issued by local authorities. In case
of emergency, the user can contact the helpline
number 333 for assistance. Stay safe!
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Figure 3: Example Output from HuggingFaceH4/zephyr-7b-beta:

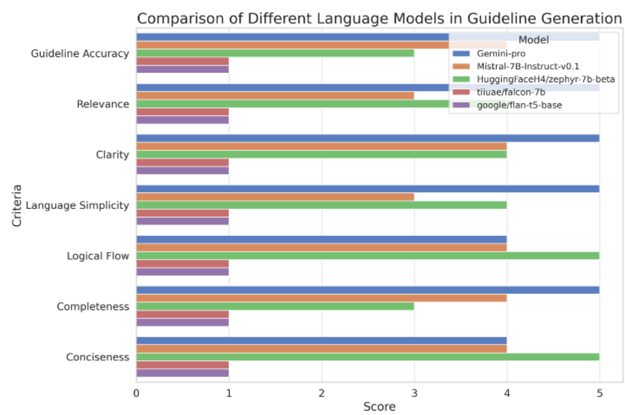

Figure 4: Comparison of Different Language Models in Guideline Generation.

outputs. More precisely, the tiiuae/falcon-7b did not provide proper guidelines but just repeated the input information without giving actionable advice. This comparison study underlines the importance of model selection with regard to appropriate applications, such as disaster warning systems, since their actual capability to handle complex inputs and produce contextually relevant outputs differs markedly.

6.3 Impact of Temperature Variation on Model Output

We also conducted further research on the impact that modification of the temperature parameter in the Gemini-pro LLM has on the quality of guidelines given. How changing the temperature levels influenced guideline quality was assessed upon six different aspects: coherence and fluency, relevance and accuracy, conciseness, creativity, clarity, and language simplicity. These are visually represented

Table 2: Scenario-based Generated Guidelines for Cyclone Preparedness.

Scenario 1
Input
Infrastructure: Weak Location Coordinate: (20°N, 88°E) Predicted Cyclone Coordinates: (19.6°N, 90.5°E), (19.9°N, 90.2°E), (20.2°N, 89.9°E), (20.5°N, 89.7°E) Predicted Cyclone Speed: 70 knots
Generated Guideline
•Prepare for evacuation: Pack an emergency bag with essential items (water, non-perishable food, first aid supplies, flashlight, batteries, important documents).
•Secure your home: Reinforce doors and windows by closing shutters or using plywood. Secure any potential hazards inside the home.
•Identify evacuation routes: Plan the route to the nearest shelter and have transportation ready.
•Stay informed: Monitor local news and weather updates for cyclone changes.
•Evacuate if necessary.
Nearest Shelter: Rajapur Government Primary School cum Cyclone Shelter, Dhansagar union, Sharankhola upazila
Helpline Number: 333
Scenario 2
Input
Infrastructure: Strong
Location Coordinate: (20°N, 92°E)
Predicted Cyclone Coordinates: (19.6°N, 90.5°E), (19.9°N, 90.2°E), (20.2°N, 89.9°E), (20.5°N, 89.7°E)
Predicted Cyclone Speed: 50 knots
Generated Guideline
•Prepare for possible evacuation: Despite strong infrastructure, be ready to evacuate if conditions worsen.
•Monitor weather updates: Stay informed about cyclone path and intensity.
•Secure your home: Reinforce doors and windows. Secure any potential hazards inside the home.
•Stock up on supplies: Have sufficient food, water, and emergency supplies for at least 72 hours.
•Establish a communication plan with family and keep emergency contacts readily available.
•Stay connected: Communicate with neighbors and local authorities.
Nearest Shelter: Nhila Burmese School cum Cyclone Shelter, Teknaf (109.0 km)
Helpline: 333

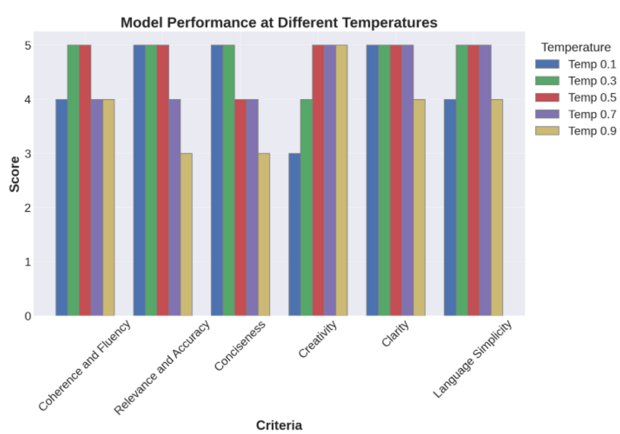

Figure 5: Model Performance at Different Temperatures.

in the bar plot that presents the performance of the model under various temperature settings.

We can see in the Figure 5 that coherence and fluency were constantly of very high quality. In particular, settings 0.3 and 0.5 presented the best from the model about those two features. There was a little loss in fluency in the lowest temperature setting at 0.1, while higher ones, at 0.7 and 0.9, just exhibited minor incoherencies due to fluctuations. Relevance and accuracy proved most secure at lower and medium temperature levels. At higher temperature settings of 0.7 and 0.9, there was a loss in relevance and a fall in precision. Of these, the lowest temperatures, 0.1 and 0.3, resulted in very concise responses, while the higher the temperature, the wordier the response became. The creativity was high from 0.5 upward, where one got truly creative responses. Clarity was strong for most of the temperature settings and only slightly deteriorated at the highest temperature 0.9, where the output became more variable. Speaking of simplicity, the most neutral outputs fell in the medium temperature ranges of 0.3 to 0.7, and both far ends-which are 0.1 and 0.9-elicited slightly more complex usages of language.

7 Conclusion and Future Work

By combining LLMs with LangChain, this project represents a transformational advancement in disaster management by overcoming the limitations of static disaster guidelines. The resulting system will allow real-time, customized guidance to be produced, thereby answering the demand for personalized suggestions in highly risky areas and improving overall preparedness against disasters.

Future research should focus on evaluating various alternative models to determine which performs best under real-time disaster conditions. Such comparative research might also examine trade-offs between model accuracy and processing speed with content variability to guide strategic model selection given the nature and complexity of the particular disaster. In sum, these endeavors achieve an integrated approach for multi-disaster response with the potential to revolutionize disaster preparedness and intervention.

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