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Optimising Crisis Management Systems Through Data-Driven Risk Communication Models: An ISM Approach to Enhancing Organisational Resilience

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ABSTRACT

Crisis Management Systems (CMSs) serve as fundamental elements in emergency response, enabling control over natural disasters, pandemics, and cybersecurity incidents. CMSs often perform inadequately when handling unstructured emergency communication and delayed messages. Frequent emergencies, along with their complex nature, necessitate response approaches that extend beyond conventional methods. The failure of traditional CMS systems to detect and organise messages promptly leads to time-consuming response delays, which in turn result in coordination breakdowns and the wider spread of false information. This study addresses these problems through a data-driven risk communication system that integrates NLP with ISM to achieve its objectives. The research utilises Kaggle's Multilingual Disaster Response data repository, which comprises actual crisis messages exceeding 30,000 entries. The text cleaning process and tokenisation, along with sentiment analysis, were performed using NLP methods before the SVM-based classification of urgent messages. The Implementation of ISM began after message classification, where urgent messages were allocated to specific hierarchical positions, with sentiment serving as a determining factor in the detection process. Evaluation standards confirmed that the model functioned effectively. Testing revealed the exceptional performance of the SVM, as it identified messages with 99% accuracy in both urgent and non-urgent categories. Only a minimal number of urgent communications needed reclassification according to the confusion matrix results. High-priority urgent messages with negative sentiment were properly identified, as most messages had a low-priority status according to the ISM-based priority distribution. The research results demonstrate that an ISM-NLP hybrid model effectively improves communication efficiency in CMSs. The crisis communication system based on this approach provides an intelligent and structured method for managing emergency responses, enabling fast decision-making and swift emergency responses.

Keywords: Crisis Management Systems, Risk Communication, NLP, Interpretive Structural Modelling, Organisational Resilience

I. Introduction

The increasing number of severe global crises presents intense challenges for organisations, governments, and humanitarian agencies to develop stronger emergency preparedness systems (Schmid and Raju, 2021). Millions of people experience displacement due to natural disasters, including hurricanes, floods, earthquakes, and wildfires, which harm worldwide infrastructure (Chaudhary & Piracha, 2021) Institutions experience major communication breakdowns during crises due to digital-age emergencies, including both cyberattacks and ruthless ransomware intrusions, as well as the all-encompassing COVID-19 outbreak, which exposed their fundamental structures for crisis management.

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Such diverse emergencies appear unexpectedly and quickly intensify, requiring unified, decisive action supported by informed decision-making to protect human life alongside economic stability and natural environments (Biswas et al., 2024). CMSs serve as the central coordination system because they enable streamlined communication, operational actions, and decisive decision-making processes during emergencies (Biswas et al., 2024).

Modern technology has advanced significantly over the last few decades, but traditional content management systems (CMSs) continue to employ reactive approaches during operations that require manual information handling (Ekanem et al., 2024). Historical control systems face limitations in managing the extensive amounts of information associated with rapidly developing crises, particularly in digital and multilingual contexts (Ekanem et al., 2024). Nonetheless, the communication flow exists as an unstructured fusion of inconsistent and delayed signals. Decision-makers face significant challenges in situational understanding because they receive excessive amounts of irrelevant data and struggle to identify crucial alerts (Munir et al., 2022). The prolonged process of analysing and ranking incoming messages produces two negative effects: it sabotages emergency operations and facilitates the spread of misinformation while diverting resources improperly. Emergency response teams face difficulties during disasters when help calls from victims are obscured by excessive non-essential information, thus complicating their triage operations (Lamberti-Castronuovo et al., 2023). Public health agencies faced challenges in managing COVID-19 real-time data during the pandemic, as they received data through various channels, including emails, social media, SMS alerts, and international briefings (Kostkova et al., 2021).

Most CMSs face primary issues beyond data shortage because they lack real-time structure in their communication operations (Han et al., 2024). Much emergency crisis information manifests as unstructured text, which includes brief messages alongside alerts and requests, as well as multilingual updates and emotional content in various forms (Luht-Kallas et al., 2023). Keyword-based data interpretation systems often struggle to effectively handle diverse crisis information, resulting in data processing delays. This communication inefficiency necessitates a paradigm shift from reactive information handling to intelligent, proactive communication management (Yue & Shyu, 2024). The proposed solution, as presented in this study, utilises Natural Language Processing (NLP) in conjunction with Sentiment Analysis and Interpretive Structural Modelling (ISM) to operate in real-time for crisis-related message classification, analysis, and priority determination (Kumar & Goel, 2022).

Through its computational processing capabilities, NLP enables the handling of vast amounts of unstructured text, which reveals meaning and selects messaging classifications according to urgency definitions or content categories (Khurana et al., 2023). Raw text data undergoes effective machine learning analysis, assisted by tokenisation, stop word removal, lemmatisation, and vectorisation methods that perform data cleaning operations (Chai, 2023). The language-agnostic nature of crisis monitoring is enabled through NLP as it assists with processing datasets from different languages, which becomes essential for global emergencies (Sarmiento Albornoz, 2023). The framework achieves additional value through sentiment analysis technology because it evaluates the emotional content of messages. The VADER tool enables the identification of panic-stricken or confused content, as well as messages that suggest distress or remaining calm, in terms of situational severity indicators. The analysis of messages with sentiment awareness proves beneficial because it reveals emotionally charged content that might seem non-urgent; instead, it indicates unrecognisable emergencies alongside psychological risks (Adesokan, 2024).

The ability to understand and classify messages established by NLP and sentiment analysis does not extend to providing structural organisation for decision-making (Wankhade et al., 2022). The

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application of Interpretive Structural Modelling (ISM) becomes crucial for this purpose. ISM establishes a systematic order among related elements through its systems-based approach, which is based on the analysis of variable relationships (Ardeshiry et al., 2024). Wealthy organisations currently utilise ISM extensively for multiple applications, yet they still need to advance its integration with artificial intelligence-driven text analytic processes (Shekhar, 2022). When used for crisis message prioritisation, ISM allows decision-makers to establish multi-level communication structures through a strategic assessment of combined variables that reflect operational decision-making chains (Shekhar, 2022).

The ISM-NLP framework initiates its operation by accessing real-world multilingual disaster response messages stored on Kaggle, which comprise over 30,000 emergency-related entries. The NLP techniques process the messages through vectorisation before preprocessing. The analysis utilises an SVM classifier to categorise messages as urgent or non-urgent, with sentiment analysis further defining these classifications through positive, negative, or neutral emotional expressions. The ISM logic engine receives the outputs and applies predefined rules to assign structured priority levels ranging from 1 to 4. The ISM logic engine assigns messages marked urgent and negative to top-priority status (Level 1) but places non-urgent, emotionally neutral messages at the lowest priority (Level 4). The completed system provides a structured message interface that crisis responders use to improve the sequence of tasks, allocate responsibilities, and escalate choices.

The integrated pipeline resolves multiple complex problems simultaneously. The system enables the instant analysis of messages from various languages, implements emotional intelligence functionality into automated systems, and establishes emergency communication priority schemes simultaneously. CMSs transition to intelligent decision-support systems through this approach, which enables them to understand and respond precisely to communication information instantly. A system of this type offers benefits that stretch past emergency response tasks. CMS applications span humanitarian aid cooperation and public health awareness distribution, as well as counterterrorism information dissemination, cybersecurity responses, and environmental threat management. Its scope encompasses every situation that requires swift, data-driven communication.

II. Literature Review

CMS & Risk Communication

Crisis Management Systems (CMSs) serve as vital tools for managing emergency response activities that occur during natural disasters, pandemics, industrial accidents, and cyberattacks (Karpiuk, 2022). CMSs serve as foundational systems that provide information exchange capabilities and resource management features, supporting time-sensitive decision-making operations even in uncontrolled circumstances (Tsavdaridis et al., 2024). Traditional CMSs have gained immense popularity among governmental agencies, humanitarian groups, and private institutions, although they continue to present noticeable limitations that limit their general usefulness (Louraço & Marques, 2022). The consistent challenge deals with how people evaluate incoming crisis-related information. Decision-makers, along with emergency responders in high-pressure situations, receive overwhelming amounts of textual information, including distress messages, aid requests, situation updates, and logistical inquiries (Reale et al., 2023). Office staff currently review and assess incoming emergency data, which both delays prompt response duration and causes them to miss key messages (Reale et al., 2023).

The complexity of crisis communication operations worsens due to their disorderly nature. Standardised message structuring does not exist during emergencies because senders base their content on their emotional state, along with cultural backgrounds and communication skills (Reale et al., 2023). The unstructured nature of emergency messages encompasses both brief, disordered statements and

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detailed written texts, which make their automatic processing challenging at large scales. The rapid spread of misinformation occurs in such environments because proper verification systems are often absent (Sun et al., 2023). Operations decisions made without message verification can lead to wrong resource allocation while spreading baseless panic within the affected populations. The absence of structure within the CMS communication workflows creates an operational bottleneck, which decreases efficiency and, in turn, endangers the fundamental stability of the crisis response (Basnawi, 2023). Researchers advocate for a change in current CMS systems that will develop them from simple reactive response platforms to smart platforms which efficiently analyse and filter data and re-prioritize according to emergency operational dynamics (Basnawi, 2023).

Interpretive Structural Modelling (ISM)

The crisis communication sector can significantly improve its performance through the supplementary implementation of the interpretive structural modelling (ISM) solution (Rafiq et al., 2021). Developed by Warfield during the 1970s, ISM functions as a qualitative assessment tool which establishes hierarchical relational models between important specific components (Hogan & Broome, n.d.). In complex decision environments, ISM provides a valuable organisational method for understanding multiple factors that depend on each other for effective action. ISM demonstrates effectiveness in the supply chain management and organisational behaviour sectors, in addition to its use for risk assessment and policy planning applications (Babu et al., 2021). ISM enables organisations to identify and manage risk elements for project management operations while also creating sustainable development structures and flexible governance frameworks (Yousef & Qutechate, 2024).

ISM achieves its strength through transforming unclear and unordered inputs into well-organized systems of related components. Where crisis communication is concerned, the ISM approach enables the organisation of messages according to their true urgency and emotional intensity while also accounting for message type (Sellnow & Seeger, 2021). Through its standardised approach, the method organises different elements of communication, from emergency alerts to resource requests and advisory updates, according to priority levels. ISM stands as a validated decision support framework, although it appears to be minimally used when processing real-time, multilingual textual information (Islam & Chang, 2021). Research has largely neglected the integration of Natural Language Processing with Information Systems Management (ISM) for crisis communication structures in both applied and academic fields. ISM holds great promise for gaining broader practical use within an area that demands quick structural solutions.

NLP in Crisis Communication

Natural Language Processing (NLP) functions as an innovative transformational technology used for analysing text-based data (Arslan et al., 2023). The interplay of artificial intelligence and linguistics enables NLP to perform a machine-based interpretation of human language, leading to automated understanding, translation, and classification processing (Mohamed et al., 2024). The field of crisis communication has adopted NLP as a primary tool over the past decade, as it effectively manages large collections of disordered textual materials. The extensive collection of text-based systems utilises NLP technology for social media surveillance, misinformation solution detection, emergency warning system automation, and humanitarian aid program organisation (Rocca et al., 2023).

The classification of messages stands as a principal application of NLP in disaster management operations. Support Vector Machines (SVMs), Random Forests, and deep learning networks, such as Long Short-Term Memory (LSTM) or Transformer models, serve as machine learning models for classifying messages into urgent and non-urgent categories or aid-related and non-aid-related content (Linardos et al., 2022). The classification tasks enable crisis responders to determine the nature of the communication and subsequently prioritise resources and mediation (Gaspar et al., 2021). Sentiment

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analysis stands out as a major NLP technique which finds numerous applications during crises. VADER, along with TextBlob, serves as an analytical tool that examines the emotional content of messages, thereby revealing panic and distress, as well as optimism, through its analysis (Linardos et al., 2022). Historical crisis management depends on emotional visibility for both human services evaluation and public messaging detection.

Current disaster response systems primarily utilise NLP for surface-level operations, including information classification and keyword extraction (Mohamed et al., 2024). Current systems implement minimal to no message structure organisation methods, which would represent their hierarchical value or relational structure. An unstructured organisational approach to crisis communication messaging processing leads to evenly prioritised treatment of all received messages. Emergency responders must infer the necessary order of message priority since the system does not provide automated assessment capabilities. The lack of a superior structural model necessitates resolution to analyse NLP outputs, as ISM presents itself as an ideal solution for this apparent gap (Abbas et al., 2022).

AI-Driven Decision Support Systems in Emergency Management

Decision support systems equipped with Artificial Intelligence enhancements have transformed critical business domains, including healthcare, finance, and logistics (Gupta et al., 2022). Emergency and disaster management organisations adopt AI-driven Decision Support Systems (DSS) because these systems extract valuable patterns from complex information and generate prompt recommendations (Shan & Li, 2024). These systems enhance crisis responder decision-making through automated processes that minimise human errors and delays while also improving awareness. The high-pressure nature of crises, combined with unpredictable scenarios, makes AI-based DSS an attractive solution that offers enhanced recommendations to address problems involving manual judgment, particularly with large amounts of heterogeneous and multilingual data (Shan & Li, 2024).

The system reviews past data in conjunction with present observations to determine disaster trajectories and evaluate risk levels simultaneously, offering suggested optimal response strategies (Khan et al., 2023). AI tools have developed various applications to monitor virus infection zones, optimise medical supply distribution routes, and efficiently disseminate pandemic-related information during the COVID-19 outbreak (Jabarulla & Lee, 2021).

AI-based DSSs in emergency contexts have gained importance, yet most instances of these systems operate independently of established decision-making organisational models (Soori et al., 2024). These systems excel in data processing and prediction; however, they cannot structure insights for hierarchical organisation, nor do they integrate with established organisational procedures (Hosen et al., 2024). AI systems generate information that differs from what crisis managers need to act effectively. ISM modelling, combined with AI systems, performs the required task of transforming basic predictions and classifications into actionable, step-by-step operational direction schemes (Hu et al., 2024).

The descriptive framework in this research work addresses industry evolution by uniting Artificial Intelligence functions with systematic Decision Support System models. The NLP-based data understanding, combined with sentiment analysis, emotional processing, and an ISM-designed decision-making algorithm, allows the framework to provide pragmatic data insights alongside organisational workflow structure (Soori et al., 2024). Through this combination approach, AI becomes a strategic asset that processes data while creating operational alignments which follow organisational targets. AI-guided DSS will define the next generation of advanced crisis response systems through their relationship with hierarchical models, such as ISM (Fetais et al., 2022).

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Gap in Literature and Practice

The partnership between NLP and ISM opens up new possibilities for developing more effective and reliable crisis management systems [46]. The technical capability of NLP to extract urgency and emotional tone from multilingual text exists, but it lacks the key infrastructure needed to develop a decision-theoretic prioritisation system. ISM establishes its information framework through structured organisation, although it does not support direct natural language processing of raw data inputs (Abbas et al., 2022). The lack of combined Information Systems modelling with Natural Language Processing systems reinforces a fundamental weakness within crisis communication practices alongside academic research about this topic. Research in this field mainly separates NLP from structural modelling analysis methods into independent academic areas. The output of NLP-based solutions typically terminates with classification tasks that label urgency levels and sentiment expressions but often skips subsequent organising tasks (Jim et al., 2024). ISM-based frameworks can only utilise manual quantitative data, which comes from surveys and expert advice (Abbas et al., 2022). The market lacks a proven model that unites NLP natural language comprehension and ISM hierarchical decision implementation through the processing of multilingual real-world datasets (Abbas et al., 2022). The crisis datasets remain underutilised in this space, even though Kaggle provides researchers with access to multilingual disaster response data, featuring extensive labelling for message classification, sentiment, and urgency assessment. The development of such a connection can revolutionise crisis message management systems. A unified ISM-NLP model enables the automatic processing and analysis of large quantities of multilingual messages in real-time operations. The implementation of such a system would reduce information overload, minimise human error, and produce more responsive and adaptive CMSs (Tsavdaridis et al., 2024). This research aims to develop and test a model that combines theoretical accuracy with practical usability.

III. Methodology

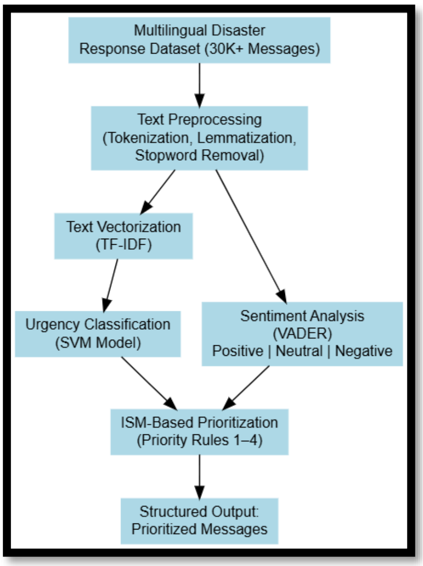

Figure 1: Proposed Methodology Diagram

The visual depiction illustrates how the proposed framework of ISM-NLP processes crisis messages. The framework utilises the Multilingual Disaster Response Dataset, which contains more than thirty thousand actual crisis-related messages. The data undergoes NLP technology-based cleaning procedures, which include tokenisation functions, lemmatisation, and stopword elimination.

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The initial phase of vectorisation applies TF-IDF to convert text into numerical values, enabling the Support Vector Machine (SVM) to classify messages into urgent and non-urgent categories. The detection of positive, negative, or neutral emotional messages occurs through the simultaneous use of VADER sentiment analysis. The ISM-based prioritisation model receives both urgency and sentiment outputs from the system to execute hierarchical rules that establish message priority standards (Priority 1 to 4). Crisis responders receive easily actionable, prioritised messages as a result of this process. The end-to-end process enables disaster response teams to manage critical, high-emotion, high-priority, and urgent communications efficiently.

Framework Overview

The research designed a structured risk communication framework using data-driven approaches, which combined Natural Language Processing (NLP), Sentiment Analysis and Interpretive Structural Modelling (ISM). The "Multilingual Disaster Response Messages" dataset, available through Kaggle, served as the foundation for implementation, as it contained a total of 30,000 crisis-focused messages in various languages. The dataset featuring crisis communication messages encompasses multiple types of emergencies, including natural disasters, humanitarian crises, and emergency help requests. Thus, it serves as an optimal platform for investigating multilingual crisis response.

The research design included NLP preprocessing to prepare the text data before employing an SVM classifier for the identification and classification of urgent messages. A sentiment scoring analysis through VADER (Valence Aware Dictionary and Sentiment Reasoner) detected emotional scope within messages. This system utilises structured priority setting to determine response and sentiment ratings based on logic derived from ISM concepts. The end-to-end system demonstrates how a Crisis Management System (CMS) works in real-world scenarios by analysing messages and determining their priority and time sensitivities through a systematic hierarchy.

This combined pipeline addresses CMS's traditional challenges by processing language data, enabling fast detection, emotional assessment, and decision-making assistance. The system achieves its goal by utilising NLP to understand inputs, employing SVM for identification, and incorporating sentiment analysis for emotional content before implementing ISM for structured prioritisation. This section examines the individual elements of methodology, providing extended explanations that ultimately contribute to achieving efficient risk communication results.

NLP-Based Crisis Message Classification

The preliminary phase of execution focused on making the dataset machine learning-ready. The data must undergo essential preprocessing steps to transform it into a suitable condition for subsequent analysis. The initial stage involved eliminating stopwords, numerical characters, and punctuation marks, followed by the processes of tokenisation and lemmatisation. A removal process targeted stopwords "the", "is", and "in" because their low semantic meaning brings excessive noise. Tokenisation separated messages into their words, while lemmatisation transformed these words into their base form, thereby enhancing the consistency and relevance of textual data. The preprocessing approach led to a substantial improvement in the data quality that the classification received.

The processed text data underwent cleaning before being converted into numerical vectors using the Term Frequency-Inverse Document Frequency (TF-IDF) technique. NLP practitioners heavily utilise the vectorisation method TF-IDF because it evaluates word frequency within documents, along with their normalised frequencies across the entire corpus. The SVM classifier gained the capacity to work with significant features after this transformation, as it operated on features rather than the raw text structure, leading to superior classification accuracy and enhanced understanding.

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A Support Vector Machine (SVM) classifier was employed to determine whether a particular message should be classified as urgent or non-urgent. The dataset was used to create separate training and testing datasets while building the performance evaluation. The developed model demonstrated 99% accuracy in distinguishing between urgent and non-urgent message types. The measured F1-score for the urgent class reached 0.97, which shows excellent precision-recall harmony. Due to this high score, the model reflects its ability to both accurately and reliably detect urgent messages that require an instantaneous response from the emergency response team.

The validation process required constructing a confusion matrix to check the classifier's robustness level. Results indicated that 16 urgent messages among 301 actual cases were misclassified as non-urgent messages. The system identified every single one of the 1,338 monitored non-urgent messages without any errors. Detecting urgent messages with accurate precision becomes crucial since crisis communication depends on avoiding any failures to detect urgent information. The combination of SVM classification methods, proper preprocessing techniques, and vectorisation methods creates an established system to detect real-time urgency in telephony crisis messaging.

Sentiment Analysis

The analysis proceeded to sentiment scoring using VADER because the tool offers exceptional capabilities for analysing brief, informal messages found in social networks and emergency response systems. Sentiment analysts utilised their scoring system to categorise every text message as positive, neutral, or negative in terms of polarity. The sentiment distribution in the dataset showed that 36% of messages were positive, 32% remained neutral, and 13% contained negative sentiment. The provided analysis delivered important details about the emotional component present within each communication.

The analysis of negative messages held primary importance because these signals typically indicate panic or distress, which are common indicators of emergencies. A message with a negative sentiment that conveys a sense of urgency signals the need for immediate priority action. The sentiment analysis function played a crucial role in preparing the information for the next stage of ISM-based prioritisation logic. When the integrated evaluation of what was said (content) and how it was said (tone) was incorporated into the system, it enhanced its capability to detect urgent emotional communications. Sentiment scoring provided human emotion intelligence to machine learning models, thereby erasing the distinction between computer opinion systems and genuine emotional understanding.

ISM Prioritisation Logic

The decision-support structure required an implementation of Interpretive Structural Modelling (ISM)-based logic that processed urgency and sentiment outputs. A rule-based variation of ISM served as the approach in this research, replacing the traditional expert-driven ISM, as it utilised classified data for defining element relationships. The system prioritised messages through an approach combining the levels of urgency with the detected sentiment values.

Each message belonged to one of four defined priority levels for classification. The system marked urgent and negative sentiment messages with Priority 1 status. Neutral emotional messages, along with urgent conditions, established themselves as the highest priority because they consisted of both intense urgency and emotional intensity. The system distributed urgent messages with no negative sentiments or positive sentiments under Priority 2 status. Messages assigned to Priority 3 lacked an immediate sense of urgency yet expressed negative sentiment, thus indicating potential issues which would be suitable for future consideration. The fourth priority included all other messages that maintained a neutral or positive tone and presented no urgency that could be deferred during a crisis.

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The message placement throughout the priority levels produced significant findings. The majority of received messages belonged to Priority 4, indicating advisory communications and other non-emotionally urgent messages. The number of Priority 1 messages composed only 5% of all transmitted messages. The real world demonstrates that high-priority occurrences are rare but require a prompt reaction from organisations. The ISM logic functioned as an information sorting system, tracking thousands of messages until it elevated crucial ones to facilitate responses from crisis managers and responders.

The research demonstrated that integrating NLP with sentiment analysis using ISM logic yields a robust tool that enhances crisis communication among stakeholders. The system enables emergency management authorities to transition from receiving basic information to making organised and informed decisions.

Implementation Environment and Tools

The complete deployment of the proposed ISM-NLP risk communication framework operated through the use of Python programming within Google Colab. Google Colab was chosen for application development because it provided flexible scalability, as well as collaborative capabilities and GPU acceleration, along with deep support for Python-based scientific library tools. The platform utilises a cloud-based notebook interface to enable instant code block execution alongside program output visualisation, which integrates with GitHub and other version control systems. Google Colab was essential because it optimally supported both the cyclical development of machine learning tasks and the management of the massive multilingual disaster response data used in this research.

The research team selected Python as their primary programming language because it supports extensive functionality for computer processing of natural language, along with machine learning capabilities and graphical data presentation. The project relied on Pandas for data handling and NumPy for numerical computations, in conjunction with NLTK and SpaCy for text preparation tasks, before utilising Scikit-learn for model training and evaluation purposes. The TF-IDF vectorisation process was performed using Scikit-learn's TfidfVectorizer, along with the SVM classifier, which was constructed from the same library. The VADER (Valence Aware Dictionary and Sentiment Reasoner) tool from NLTK was used for the sentiment analysis of emergency message texts, as it has been successfully applied to short, informal texts.

A custom Python rule-based engine generated priority levels from the integration point, utilising urgency and sentiment analysis through standard coding elements and conditional evaluation operations. The graphical analysis solution included bar charts, alongside histograms and classification reports, as well as confusion matrices, which were generated using Matplotlib and Seaborn for result validation and easy understanding. Implementation transparency, along with easy experimentation, became possible through Google Colab because the tool provided an interactive platform where text and code integrated with output displays in a single document.

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IV. Result

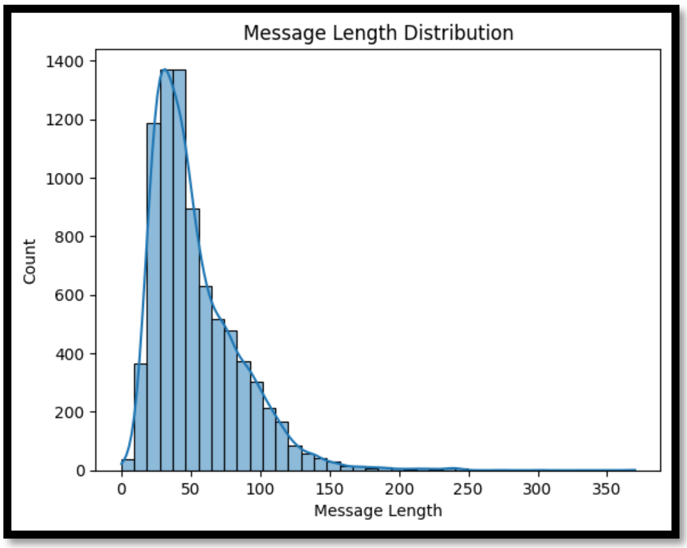

Figure 2: Message Length Distribution

Figure 2 presents a graphical presentation of disaster response message text lengths. Most text entries fall within the 30- to 50-character range, which is the most commonly observed message length. A positive skew emerges from the histogram because extended messages occur with decreased frequency. During crises, people form brief and specific messages due to the immediate needs and the requirement for clarity. The optimisation of NLP models requires knowledge about message length, as it affects vectorisation methods, as well as transformer and deep learning-based approaches, which have limitations with long text inputs.

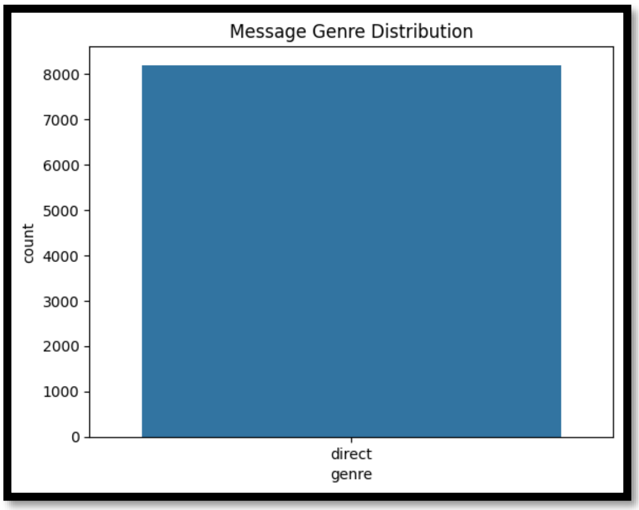

Figure 3: Message Genre Distribution

The analysis depicts that the "direct" genre contains all communication messages throughout the dataset. These findings suggest two possibilities regarding the dataset: one in which all crises originated from direct user reports, and the other in which preprocessing steps removed communication types beyond user reports (Figure 3). The lack of diversity in communication genres

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reduces the ability of trained models to apply their learned patterns in different channels. The direct communication analysis for emergency requests, along with alerts, still finds strong alignment with this dataset because it directly supports the main purpose of organising urgent, multilingual crisis messages.

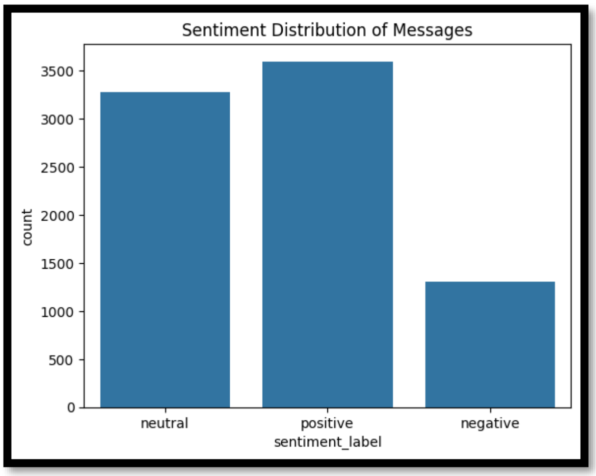

Figure 4: Sentiment Distribution of Messages

According to this chart, positive messages coexist alongside neutral messages, as well as negative messages, which it categorises. Overall sentiments are evenly distributed among messages, with positive sentiment holding the highest position, neutral sentiment maintaining a similar level, and negative sentiment standing at a minority (Figure 4). The detection of negative sentiment plays a vital role, as time-sensitive issues often manifest with such emotions in ISM-based prioritisation models. Readers can prioritise faster response to critical messages by understanding the emotional tones included in communication channel contents. The high number of neutral and positive messages indicates that panic-driven communication does not dominate crisis exchanges, while advisory information constitutes a significant portion of the content.

Classification Report:

	precision	recall	f1-score	support
0	0.99	1.00	0.99	1338
1	1.00	0.95	0.97	301
accuracy			0.99	1639
macro avg	0.99	0.97	0.98	1639
weighted avg	0.99	0.99	0.99	1639

Figure 5: Classification Report (Urgency Detection Model)

An evaluation report assesses the performance levels of an SVM model that distinguishes urgent (1) messages from non-urgent (0) messages. The trained model achieves 99% accuracy, demonstrating excellent detection capabilities for non-urgent messages, along with high precision and recall. The F1-score potency remains at 0.97, despite a slight decrease to 0.95 in urgent message recall (Figure 5). The model proves effective in detecting critical communications, as evidenced by its ability to identify high-priority messages accurately. The model exhibits reliable performance, as evidenced by its high macro and weighted averages, ensuring its suitability for use in structured communication networks.

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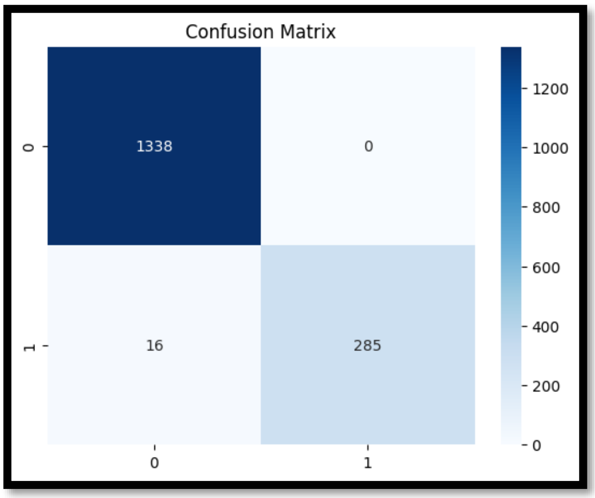

Figure 6: Confusion Matrix

The SVM model demonstrates outstanding performance, as indicated by the data presented in the confusion matrix. Of 301 genuine urgent alerts in the database, the prediction model accurately identified 285 and mistakenly identified 16 as non-critical communications. The SVM model correctly diagnosed every one of the 1,338 non-urgent messages out of a total of 1,338 cases. The model demonstrates a stronger ability in terms of non-urgent case prediction, as such cases constitute the majority in imbalanced datasets (Figure 6). The wrong classification rate for urgent messages remains at an acceptable level. The detection accuracy of urgent messages during crisis communication is critical as a small number of actual urgent messages identified as non-urgent would be significant, thus requiring additional tuning or ensemble methods to maximise sensitivity.

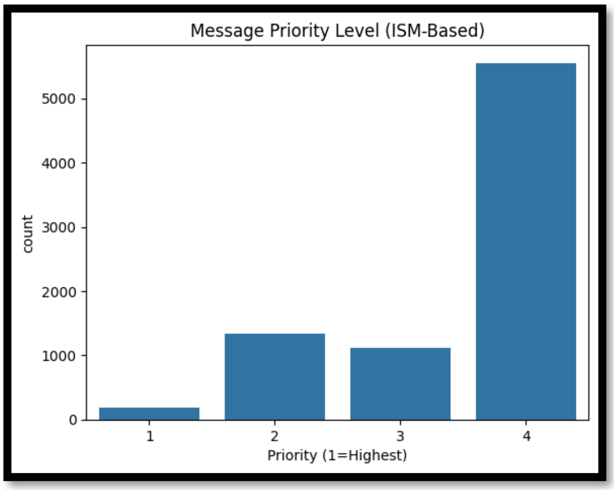

Figure 7: Message Priority Level (ISM-Based)

The visual representation uses bars to display the priority ratings determined through the ISM-based structuring framework. The Level 4 category prevails, indicating that most messages lacked an urgent nature and emotional negativity. Most of the messages received medium concern designations (priority positions 2 and 3), though priority designation 1 marked a small percentage of messages with high urgency and intense emotions (Figure 7). Such structured prioritisation demonstrates that

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sentiment analysis, along with urgency classification, produces effective results. The structured approach enables crisis responders to begin with the most critical messages, which speeds up response times and improves coordination efforts, ultimately leading to reduced information processing issues during emergency decisions.

V. Discussion

The combined use of NLP and sentiment analysis with ISM in the proposed framework brought various essential advantages to technical system performance along with practical crisis communication capabilities. The primary benefit of this framework stemmed from its ability to reduce the mental stress affecting crisis response team members. The normal operation of traditional CMS systems requires responders to analyse numerous unstructured text messages, which may contain redundant and non-essential information or be unimportant. This framework facilitated message analysis through real-time automated message assessment, prioritisation, and classification. The defined operational process enabled decision-makers to concentrate on critical messages, which helped them respond effectively in urgent situations.

The implementation of ISM prioritisation functions serves as an effective tool for managing coordination between response levels. The system organised messages according to dual criteria, allowing it to establish an alert framework that followed established organisational work procedures. High-priority messages labelled as Priority 1 could be immediately directed to senior crisis managers because they met both urgent and emotionally negative criteria, and Priority 4 messages could be addressed later by support staff through asynchronous methods. The structural decision-making system improved operational performance while minimising misunderstanding through its channels, which remains crucial when severe stress conditions could result in inefficient actions.

The framework delivered sentiment-aware structuring, which became a main advantage during implementation. The sentiment analysis feature helped detect fear-filled and distressing messages, as well as separate advisory messages from urgent emotional help requests. The model utilised sentiment analysis to enhance its understanding of urgent messages, enabling it to distinguish between what was important and what was emotionally significant. It is essential to recognise emotional Arrows during emergency events because charged language signals possible danger or audience exposure to threats. Through its mechanism for detecting the emotional context, the framework achieved higher reliability in its priority processing function.

The implementation results support the findings detected earlier. Most crisis communications remained brief in length, indicating that they could be efficiently accommodated by NLP preprocessing and vectorisation processes. The concise nature of crisis communications enabled the streamlined design of the model while maintaining performance standards. Most crisis messages fell under the "direct" genre, indicating that the collected data primarily consisted of field reports. This uniformity in genre types made modelling simpler, yet it poses restrictions for applying the model across different communication methods beyond crisis reports.

Chart analysis showed that positive and neutral comments transcended negative statements during the study period. Virtual Disaster Response Research reveals that many crisis-related messages convey more peace than panic, so models require precise adjustments to their urgency rules to avoid classification errors. The result metrics demonstrated that the NLP-SVM model had strong classification capabilities. The analytical model accurately detected urgent messages with 99% accuracy, achieving an F1-score of 0.97 in the urgent class. The confusion matrix revealed 16 incorrect urgent classifications out of a total of 301 critical cases, thus indicating small-scale practical misclassification errors.

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The analysis of distribution results through ISM demonstrates an accurate representation of actual crisis communication patterns. A majority of the distributed messages received low-priority labels, while the total number of high-priority messages remained minimal. The frequency of critical crisis communication aligns with nature, as such urgent emotional messages are rare occurrences. The operational worth of the ISM model becomes evident because it detects critical messages while avoiding system congestion.

The framework has certain disadvantages despite its functional capabilities. The limited types of text content covered by the framework may create potential restrictions when applying it to data from multilingual social media or broadcast alerts. Real-time deployments would encounter important consequences from even one ignored urgent case, although misclassifications remained minimal. The practical restrictions outline potential enhancements for future expansion.

VI. Future Research Directions

The current implementation of the ISM-NLP risk communication framework has demonstrated its capabilities in multiple settings; however, future research projects will enhance its scalability and adaptation potential, ultimately improving its performance levels. API technologies prove to be one of the most promising tools when integrating real-time data streams into systems. The system could better serve emergency managers by having access to live crisis-related messages from Twitter through the Twitter API as part of an extended pipeline framework. Such integration would enable the model to monitor dynamic evolving situations and enhance its value in modern disaster response operations.

The system incorporates blockchain functionality to establish an encrypted database that securely logs crisis communications. A tamper-proof systemic communication record would establish transparency through accounting, ensuring the integrity of crisis data after transmission and preventing any unauthorised modifications. Verifiable audit trails representing all communications and action sequences would benefit governmental and intergovernmental crisis response teams according to their requirements.

Multilingual expansion is also critical. The study contains multilingual messages in its dataset, although the NLP pipeline operates best with English language data. The system requires enhancement through the integration of translation systems based on MarianMT and M2M100 to achieve linguistic extension capabilities. The system would handle message analysis with consistent results and global message prioritisation using this approach.

ISM structuring will become more effective when human experts validate information during this phase, thereby improving accuracy and adaptability. The system gains improved context awareness in decision-making through domain expert reviews and the modification of prioritisation rules, which help it learn from expert assessments. These future directions aim to develop a robust communication management system that can be deployed across all universes.

VII. Conclusion

The research developed an innovative framework that enhances CMS risk communication features by combining NLP with sentiment analysis, along with ISM components. The increasing rates of global risk development have been shown to exceed the manual information management capabilities of systems that use standard classification methods and human message screening processes. This research introduced a system that utilised AI technology to develop a structured communication pipeline, solving existing CMS architecture problems by promptly assessing, categorising, and analysing the emotional content of disaster response messages across multiple languages.

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The proposed system utilised the Kaggle Multilingual Disaster Response Messages dataset, which comprises over 30,000 multi-language emergency-related texts. The system processed the diverse message entries by running a detailed NLP preprocessing sequence, which included tokenisation, lemmatisation, and stopword extraction, to prepare them for machine learning processing. A Support Vector Machine (SVM) classifier achieved exemplary results in message classification tasks, reaching an accuracy level of 99% and an F1-score of 0.97 for urgent message detection. The model performed reliably in crucial emergencies, as indicated by a confusion matrix testing that yielded few incorrect negative results.

The study employed VADER sentiment analysis to enhance emotional detail in urgency classification through a system that determined message polarity as either positive, negative, or neutral. The system gained the ability to recognise intense emotional messages in addition to basic urgency detection through this update because such communications might reveal hidden risks or psychological distress. Sentiment trends from the crisis messages helped researchers define more effective crisis message prioritisation strategies while preventing unnecessary reactions to peaceful content.

The ISM-based prioritisation layer distinguished itself as the main innovation by consolidating urgency analysis outcomes with sentiment results to establish specific priority classifications that MessageWatch applied to each communication. The message classification system created four priority levels, stating that both urgent messages carrying negative emotional content ranked as Priority 1 at the top level while Priority 2 encompassed urgent messages with neutral or positive sentiment and negative yet non-urgent messages formed Priority 3, and all remaining messages except Priority 1 through 3 were assigned to Priority 4. A systematic model provided CMS with improved workflow effectiveness and efficiency, as it enabled the rapid delivery of crucial messages while effectively managing lower-priority content.

The framework demonstrated its effectiveness by generating display outputs that displayed its performance. The EDA plots revealed that almost all messages employed a direct genre format with concise content, which facilitated easier processing. The analysis of sentiment distribution proved its effectiveness because negative messages were fewer but more likely than positive or neutral ones to warrant urgent attention. The final distribution of ISM data closely resembled the actual emergency response model, indicating that most reports could be addressed later, but a small subset required an immediate response.

While the study's success was noted, the authors recognised two main limitations associated with the low number of contained genres in the dataset and potential misclassification risks for urgent messages. The identified points need careful attention for forthcoming developmental initiatives. The ISM-NLP framework provides essential components that support large-scale instant communication systems, enabling them with emotional intelligence.

This research demonstrates that emergency response operations benefit from a combination of AI-powered CMS and the structured ISM decision-support model, as it improves response speed while also enhancing accuracy and context-based relevance. The system's capability to connect unstructured linguistic inputs to structured decision outcomes enhances organisational resilience and accelerates humane crisis interventions during emergencies.

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