JOURNAL OF DATA SCIENCE | Vol.2024:43
eISSN:2805-5160

The Analysis of Resilientnet-Realtime Disaster Response System

Supriya Kamoji[1], Heenakausar Pendhari[2], Kris Corriea[3], Mathew Lobo[4], Hisbaan Sayed[5], Omkar Satupe[6]

[1-6]Department of Computer Engineering, Fr. Conceicao Rodrigues College of Engineering, Mumbai, Maharashtra

Email: supriyas@frcrce.ac.in[1], heenak.pendhari@fragnel.edu.in[2], crce.9185.cs@gmail.com[3], crce.9204.cs@gmail.com[4], crce.9432.cs@gmail.com[5], crce.9232.cs@gmail.com[6]

Abstract

Responding to India's urgent need for effective disaster management, proposed framework ResilientNet, an innovative system leveraging real-time big data processing and advanced AI technologies. ResilientNet gathers diverse multimedia content from a wide range of social media services, including Twitter, Instagram, Facebook, etc., and utilises the GEMINI API, enabling comprehensive analysis and verification. Data is stored in the NEO4J database and visually represented on a user-friendly website dashboard for easy accessibility and insights. This research explores the efficacy of crowdsourced fact- checking, contributing to a novel disaster-focused tweet verification system. ResilientNet's amalgamation of crowdsourcing and AI creates a comprehensive graph of critical metrics and trends, enabling authorities to counter misinformation and direct disaster response efforts efficiently.
.

Keywords

BERT, Disaster Management, Knowledge Graph, NEO4J Database, Tweet Classification and Verification

Introduction

Given the complexity of disaster management, particularly due to the rapid spread of misinformation, this research paper introduces **ResilientNet**, an advanced framework aimed at revolutionizing India's disaster response capabilities (Shah et al., 2019; Sufi, 2022). ResilientNet combines crowdsourced fact-checking, cutting-edge artificial intelligence (AI), and real-time big data processing to address existing gaps in disaster response (Khajwal et al., 2022; Alam et al., 2018). By focusing on information accuracy and closing gaps in disaster reporting, ResilientNet establishes an adaptable, cohesive system that supports precise disaster assessment and coordinated response efforts (Son et al., 2021). As India continues to advance its disaster management strategies, ResilientNet exemplifies innovation, representing both technological advancements and a paradigm shift in disaster resilience (Mohanty et al., 2021; Pathan, 2020).

Submission: 24 July 2024; **Acceptance:** 28 October 2024

To ensure effective disaster management, ResilientNet leverages state-of-the-art AI and real-time data processing to power data visualization and real-time disaster assessment, employing sophisticated fact-checking tools integrated with social media analysis (Shah et al., 2019; Boné et al., 2020). By providing authorities with actionable insights to counter misinformation, ResilientNet enhances disaster response coordination, transforming the landscape of disaster management with AI and crowdsourced verification (Sreenivasulu & Sridevi, 2021; Priyanka & Thangavel, 2020). ResilientNet's mission is to inaugurate a new era of disaster preparedness and response in India, encouraging timely and well-informed decision-making (Fang et al., 2014; Sun & Scanlon, 2019).

Key Findings of the Research

- **Develop the ResilientNet Framework**: ResilientNet offers an integrated platform using real-time big data processing, advanced AI algorithms, and crowdsourced fact-checking to improve disaster management (Salh et al., 2021).
- **Data Aggregation and Verification**: Efficient aggregation and analysis of multimedia content from Twitter and other sources are achieved using GEMINI APIs, enhancing the credibility of disaster-related information (Sreenivasulu et al., 2021).
- **NEO4J Database Integration and Visualization**: The NEO4J graph database stores and visually represents aggregated data, offering authorities a user-friendly dashboard to access actionable insights and monitor real-time trends (Lwin et al., 2019; Kankanamge et al., 2020).
- **Accurate Location and Severity Assessment**: Advanced algorithms enable precise disaster location identification and severity assessment, helping authorities make informed decisions (Zhang et al., 2020).
- **Dynamic Querying in NEO4J**: ResilientNet's functionality is enhanced through dynamic querying within the NEO4J database, allowing authorities to extract relevant information efficiently for tailored response strategies (Ren et al., 2021; Zaidan et al., 2022).

The paper's structure is as follows: Section 2 explores current state-of-the-art disaster management techniques (Zou et al., 2021). Section 3 describes the proposed ResilientNet framework and the dataset utilized for disaster risk management. Section 4 presents evaluation results and experimentation details, while Section 5 concludes the research with a summary and future directions.

Methodology

A. Overview of the Project

The **ResilientNet** framework consists of several specialized modules designed to enhance disaster management using advanced technologies. Each module contributes a unique function to improve data accuracy, streamline processing, and facilitate decision-making, ultimately supporting a robust disaster management system.

Fact-Checking Module: This module integrates GEMINI into a React application to verify user-provided statements from Twitter data. It transmits input to GEMINI for analysis, determining the truth value of the content, and generates fact-checking reports to foster a more trustworthy digital environment. Fact-checking plays a critical role in disaster management by reducing misinformation and supporting accurate data dissemination (Kamoji & Kalla, 2023; Khattar & Quadri, 2022).

Preprocessing Module: This module refines Twitter data by removing non-essential elements like hashtags and emoticons, ensuring that subsequent analysis operates on the most relevant content. By minimizing noise in the dataset, the preprocessing module enhances the accuracy of analytical processes (Bisht et al., 2022; Alzoubi, 2022). Effective preprocessing is crucial in disaster response to ensure that actionable information is extracted efficiently (Shen et al., 2020).

Classification Module: Utilizing the DistilBERT model, this module classifies tweets as either disaster-related or non-disaster-related, and further distinguishes between informative and non-informative tweets. This classification ensures that only actionable disaster-related information is prioritized, allowing responders to focus on critical data (Zou et al., 2021; Misba et al., 2023).

Named-Entity-Relationship (NER) Module: Leveraging spaCy for Named Entity Recognition (NER), this module quickly and accurately extracts relevant information from tweets. spaCy's speed, customization, and pre-trained models enable rapid information extraction, which is vital for timely decision-making in disaster management (Fahim & Sufi, 2022; Liaqat et al., 2021). By identifying key entities and relationships, this module aids in organizing information crucial for disaster response efforts.

NEO4J Database and Visualization Module: This module uses Neo4j as a graph database management system to represent the interconnected data within disaster management. The Neo4j system enables intuitive modeling of disaster-related entities and relationships, facilitating real-time updates, historical data analysis, predictive insights, and collaboration among disaster responders (Gebremeskel et al., 2021; Saoud et al., 2022). Through real-time visualization and a user-friendly dashboard, this module supports efficient decision-making and resource optimization in disaster response (Son et al., 2021).

Together, these modules create a cohesive ResilientNet framework that enhances disaster management through efficient data processing, accurate information classification, and reliable visualization tools. The integration of technologies such as GEMINI, Neo4j, and spaCy in ResilientNet positions it as a cutting-edge solution in disaster resilience, equipping responders with actionable insights and tools to make informed, timely decisions (Gao et al., 2021; Hamdoun et al., 2021).

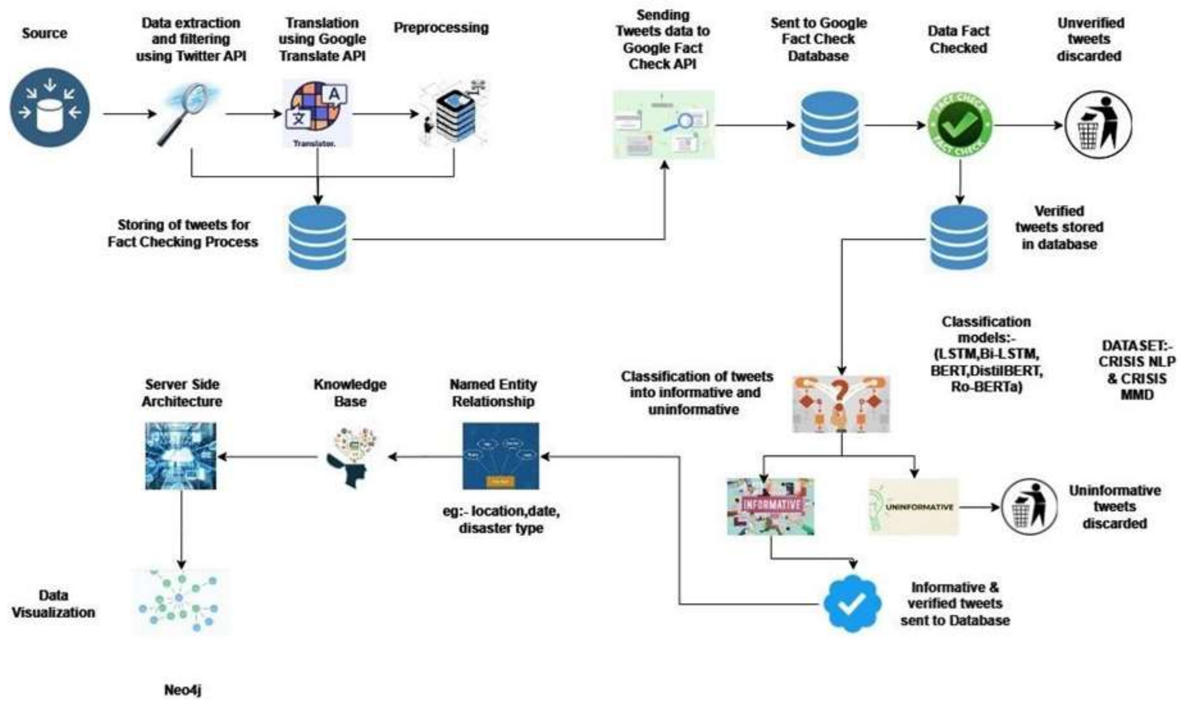

Figure 1. Framework Architecture

Highlights and proposed Methodology

1. Extracting tweets from Twitter using the Twitter API. Creating a Twitter developer platform for this purpose. Using real time tweets from Twitter.
2. After extraction, data cleaning processes are performed. Converting all the tweet data into English using Translate API.
3. After converting to English, Fact checking the tweet data using GEMINI, using classification algorithms to classify tweets into informative and non-informative.[11], [24]
4. Extracting disaster-related informative data from the tweet.
5. Integrate it with neo4J.
6. Graphic visualization of the real-time data.

B. Module Description

1. Fact-Checking Module

A React application module that verifies and validates user-supplied information via the Gemini API. The objective of this module is to bolster the credibility of the digital environment through the verification of information that is encountered.

The constituents:

1. User Input Gathering: Individuals provide assertions, data, or claims for the purpose of fact verification, with the possibility that they indicate Twitter as the originating platform. This input is collected by the React application prior to its transmission to the Gemini API.

2. Integration with Gemini API: The React application transmits the user's input to the Gemini API for the purpose of analysis. To establish a connection with Gemini, employ the Google AI-provided Gemini API.
3. Response Processing: Analyse and assess the Gemini responses that have been received. Extract pertinent information, claims, or expressions from the output of the model.
4. Fact-Checking Algorithm: Utilise the functionalities of Gemini to validate the data against reputable sources, which may include Twitter if the user so specifies. Construct a fact-checking algorithm that utilizes Gemini's analysis to evaluate the veracity of the user-supplied statement. Based on the analysis, ascertain the truth value (true, false, uncertain, informative/non-informative). Potential use of the database-stored results in training future fact-checking models.

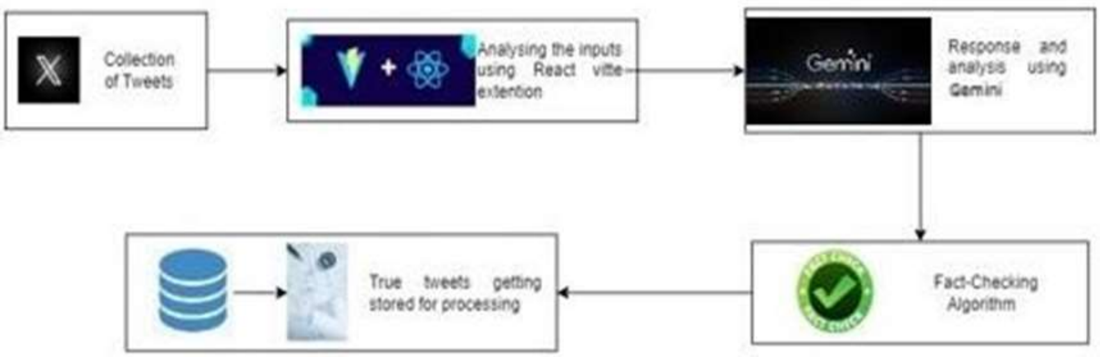

Figure 2. Framework Architecture

2. Preprocessing Module

In the **ResilientNet** framework, the **Preprocessing Module** serves as a crucial component for managing the vast influx of Twitter data and effectively identifying disaster-related information. During the initial phase of preprocessing, the focus is on refining tweet content by removing non-essential elements such as hashtags, emoticons, and irrelevant text. This step is critical in distilling essential information, ensuring that subsequent analytical processes operate on meaningful, relevant data, which enhances data quality and reduces noise within the dataset (Sreenivasulu et al., 2021; Kankanamge et al., 2020). This meticulous preprocessing contributes to data cleanliness, a foundational step in accurate disaster assessment.

The design of ResilientNet's preprocessing module was significantly influenced by **CrisisMMD**, which offers extensive coverage of disaster-related multimedia content on Twitter, including both natural and man-made disasters such as floods, earthquakes, wildfires, accidents, conflicts, and industrial incidents (Alam et al., 2018; Zhang et al., 2020). CrisisMMD's diverse disaster scenarios enhance ResilientNet's capacity to analyze a wide range of disaster events, enabling comprehensive and adaptable disaster response. Furthermore, CrisisMMD provides annotated data, which is instrumental for supervised learning and enhances ResilientNet's algorithms in accurately identifying disaster-related information in Twitter data (Shah et al., 2019; Ren et al., 2021). These annotations allow ResilientNet to better inform disaster management authorities by improving its data filtering and classification capabilities.

By incorporating CrisisMMD's rich dataset, the preprocessing module within ResilientNet is optimized for real-time social media analysis, aligning with the framework's objective of enhancing disaster management through timely, accurate insights. This integration allows

ResilientNet to identify and process relevant social media content, empowering disaster management authorities with precise information and facilitating a swift, informed response (Priyanka & Thangavel, 2020; Boné et al., 2020).

3. Classification Module

The classification module constitutes the categorization of tweets along two crucial dimensions: disaster- related versus non-disaster-related, and informative versus non-informative. Leveraging the DistilBERT model, tweets are initially classified as either disaster-related (target: 1) or unrelated (target: 0). The selection of DistilBERT is based on its efficiency and effectiveness, retaining much of the performance of its larger counterpart, BERT, while significantly reducing computational requirements. This makes it practical for processing vast volumes of tweets in a real-time disaster response scenario. Moreover, DistilBERT excels in comprehending contextual information in text, a vital attribute for accurately classifying disaster-related tweets and distinguishing between informative and non-informative content.

This binary categorization serves as the primary filter for identifying tweets relevant to disaster situations. Subsequently, within the subset of disaster-related tweets, a more nuanced classification is carried out to differentiate between informative tweets offering actionable information about disasters and non-informative tweets that may contain metaphorical or extraneous content. This module's significance lies in ensuring that only pertinent and actionable disaster- related information is retained, thereby augmenting the system's capability to validate and prioritize such data from Twitter's extensive dataset.

4. Theoretical Analysis of Algorithms Used

Table 1. Theoretical Analysis of Algorithms Used

Algorithm	Key Features	Advantages	Efficiency
LSTM	Sequential data processing	Captures sequential patterns in text	Computationally
Bi-LSTM	Bidirectional sequential processing	Considers context from both directions	Moderate
BERT	Pre-trained transformer- based model	Captures contextual understanding	Relatively slower
RoBERTa	Enhanced version of BERT	Improved pre-training process	Slower than DistilBERT
DistilBERT	Lighter and faster version of BERT	Retains much of BERT's performance	Efficient and faster

5. Named-Entity-Relationship Module

SpaCy for Named Entity Recognition (NER) in ResilientNet is strategic for disaster management [28]. Due to its customised NLP, SpaCy excels in tokenization, part-of-speech labelling, and named entity recognition. BERT is known for contextualised embedding, but its extensive architecture may be too much for NER, where spaCy excels. SpaCy's speed and lightweight implementation match emergency management's real- time needs. SpaCy's adaptability is ideal for processing a large number of tweets quickly. A well-documented API makes it user-friendly for researchers and developers, making it a practical choice for targeted NLP tasks.

SpaCy's pre-trained named entity recognition models, which include date, time, and location, greatly reduce model training effort. This skill is ideal for disaster management, where fast and accurate information extraction is crucial. SpaCy's integration goes beyond NLP. ResilientNet stores and retrieves data in NEO4J, and SpaCy's seamless integration with other tools and databases makes it a better option than BERT in NLP pipelines. SpaCy is a wise choice for ResilientNet's Named Entity Recognition module. The combination of speed, user friendliness, pre-trained models, and integration capabilities is ideal for disaster management.

6. Neo4j Database and Visualization Module

Neo4j, as a graph database management system, plays a crucial role in disaster management systems due to its unique capabilities, which precisely correlate with the complex and interconnected nature of disaster response and recovery efforts. Neo4j's capacity to represent data as a graph, with nodes representing entities and relationships representing their connections, is fundamental to its operation.

This graph-based approach allows for the intuitive modelling of complex and interrelated components in disaster management, such as locations, resources, victims, and response teams. Neo4j excels at efficiently managing these relationships, allowing respondents to make well-informed decisions regarding resource allocation, coordination, and response strategies. In addition, Neo4j's geospatial capabilities make it ideally suited for disaster management because it can effectively manage spatial data, such as the locations of afflicted areas, resources, and infrastructure.

This allows first responders to conduct geospatial analyses and make location-based decisions in real time. In disaster management, resource optimisation is another crucial Neo4j function. By tracking the availability of resources and allocating them to areas in need, the system ensures an effective response. Real-time updates are managed without a hitch, enabling access to the most current and accurate information, a necessity in the dynamic context of disaster response. In addition, Neo4j allows for the storage and analysis of historical data pertaining to past disaster incidents, response efforts, and outcomes.

By analyzing historical incidents, responders can learn from experience, identify best practices, and make data-driven enhancements to future response strategies. Neo4j's graph algorithms and query capabilities also enable predictive analysis, enabling responders to forecast the potential spread and impact of disasters and devise mitigation strategies. Neo4j's ability to represent communication channels and hierarchies within the graph facilitates collaboration and communication, thereby promoting effective coordination among various organizations and agencies involved in disaster management.

Although Neo4j does not provide native role-based access control, application logic can be used to implement access control mechanisms, thereby enhancing data security and privacy. In conclusion, Neo4j's capabilities enable disaster responders to more effectively manage complex, interconnected data, thereby facilitating decision-making, resource optimisation, and overall disaster management efforts.

Results and Discussion

System Performance Evaluation

To evaluate the proposed system, disaster-related tweets are categorised and flood-related information is extracted. By comparing disaster tweet classification algorithms to existing systems, model evaluation metrics are utilised. Extraction of flood knowledge requires the visualisation of local and global system behaviour.

A. Factchecking

The fact-checking module output pic for the research paper presents a comprehensive report detailing the veracity of user-provided statements or claims. Through integration with the Gemini model and meticulous evaluation against reliable sources such as Twitter, the module delivers insightful assessments of the information's accuracy.

The output depicts the truth value of the statement, categorizing it as true, false, or uncertain, and provides supporting evidence or sources to substantiate the determination. This output not only fosters transparency and accountability in the digital space but also empowers users with trustworthy information, contributing to a more credible and reliable online environment.

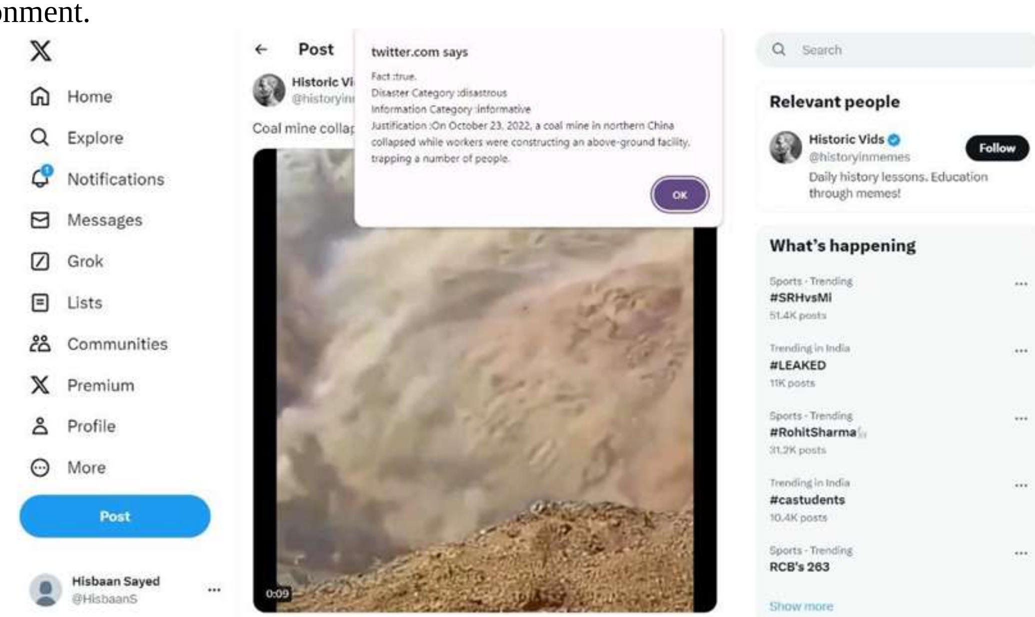

Figure 3. FactCheck output

B. Disaster Tweet Classification

The F1-Score, the most widely used metric for text categorization, is employed to compare the models. In information retrieval, this metric, which combines precision and recall, is utilised to estimate incorrectly classified cases more accurately than accuracy. The individual dataset classification experiments utilised CrisisMMD because of its substantial size and extensive set of class labels, which consisted of two, six, and eleven. For the sake of consistency, categorization tests from the train, development, and test datasets are chosen. To determine whether smaller datasets are effective, the model is trained on them and then evaluated on the combined test set.

Table 2. Comparative results of Accuracy, Precision, Recall and F1 Score

Sr. No	Algorithm	Accuracy	Precision	Recall	F1 score
1.	LSTM	0.85	0.82	0.87	0.84
2.	Bi-LSTM	0.87	0.85	0.88	0.86
3.	BERT	0.88	0.87	0.87	0.85
4.	RoBERTa	0.89	0.88	0.86	0.87
5.	DistilBERT	0.91	0.92	0.91	0.89

Table 3. Comparative analysis of our proposed model with state of art techniques results Crisis MMD dataset

Ref no	Model Used	Accuracy	Precision	Recall	F1 score
[24]	RCNN	-	-	-	76.75%
[27]	FastText	85.2%	86.3%	85.2%	85.8%
[26]	BiLSTM	72.80.1%	63.72%	62.13%	62.03%
Proposed Model	DistilBERT	91%	92%	91%	89%

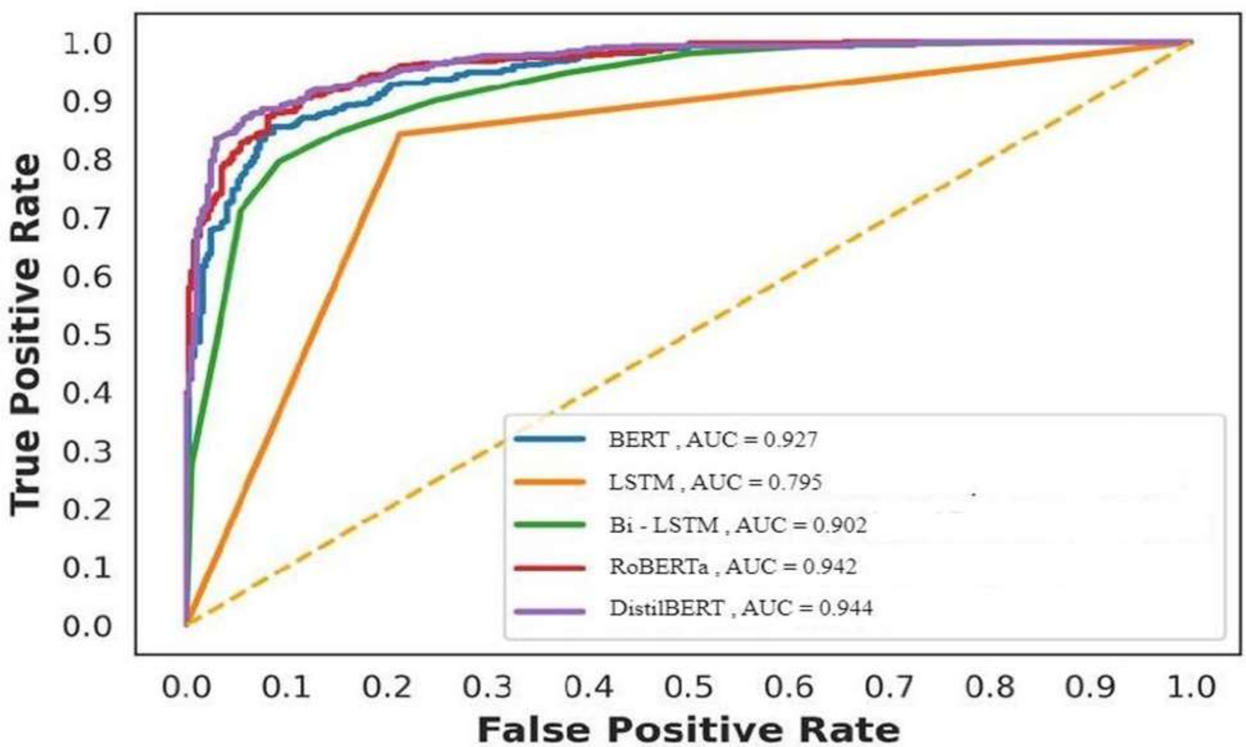

Figure 4. ROC / AUC for algorithms used

C. Evaluation Using Knowledge Graph

Imagine extracting crucial insights from the ever-flowing river of tweets in real-time. This system demonstrates just that, showcasing the journey from tweet retrieval and classification to information extraction and visualization within a comprehensive Knowledge Graph. While designed for live operation, simulation is done using 500 pre-loaded tweets, categorized informativeness, and extracted key entities with Spacy's NER. As the tweet volume increased from 15 to 500, the Knowledge Graph gracefully expanded, highlighting its scalability and readiness for real-world data volumes. This opens the door to unlocking valuable insights from the vast social media landscape, one tweet at a time.

Figure 5. Knowledge graph after 15 tweets

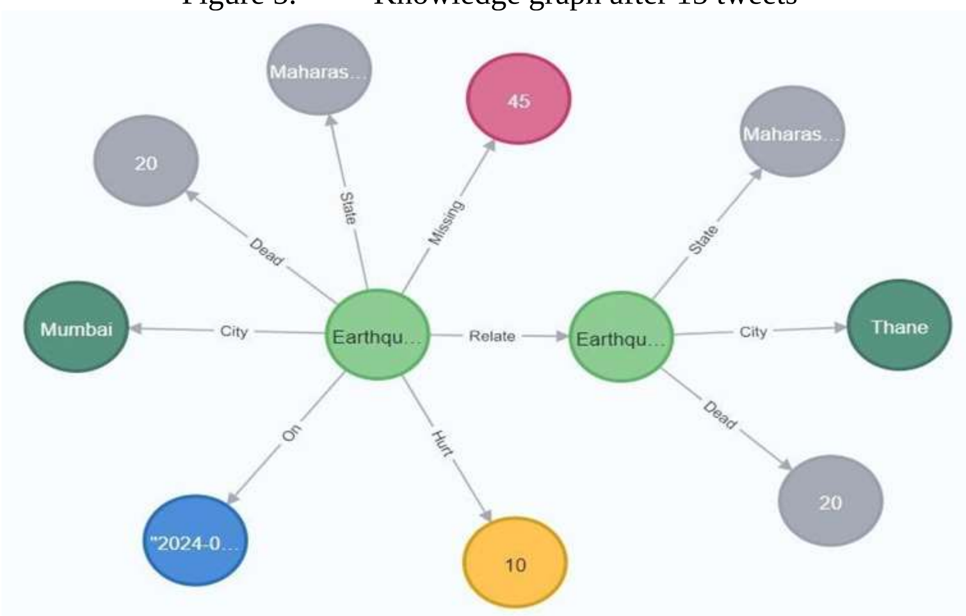

Figure 6. Knowledge graph after 50 tweets

The system kicks off with just 15 processed tweets, generating a basic Knowledge Graph (Figure 4.3.1). This graphmanagents a central node representing the initial earthquake event and five connected nodes holding various attributes. Figure 4.3.2 reveals what these neighbors signify: state, city, date, injured, and missing people. This extracted information, thanks to a custom Spacy NER model, equips decision-makers with immediate awareness of the disaster, its location, date, and initial impact.

As more tweets roll in, existing nodes in the graph dynamically update based on new information. Figure 4.2.2 shows the impact of 50 tweets: the earthquake node sees its casualty numbers rise, and a new "deaths" node even emerges. Meanwhile, a completely separate disaster, also starting on the same date, pops up on the graph with its own location and impact details. This seamless evolution from 15 to 50 tweets showcases the system's impressive ability to handle live data feeds, continuously refining its picture of unfolding events in real-time. Each tweet serves as a tiny brushstroke, contributing to a bigger, clearer understanding of the disaster landscape.

Each new disaster will have its own node and information about the disaster like location, injured, dead etc of each disaster will have their own node in the database. The database will keep on updating as and when new tweets about different disasters arrive. With the help of the dashboard, anyone can perform various queries. For instance, the disasters occurring at a particular location (state) for a particular time frame.

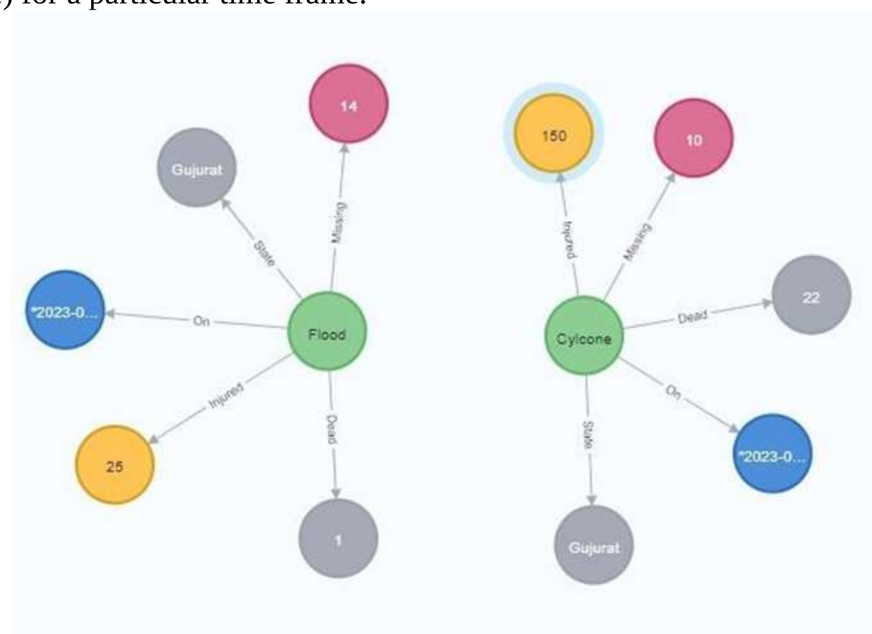

Figure 7. Disasters in Gujarat in 2023

Considering another state, Kerala, for 18th October 2023, a flash flood occurred there. Furthermore, data about the different disasters that have occurred in a particular state for a given timeline can be found. For instance, the amount of disasters occurring in Maharashtra for the year 2023.

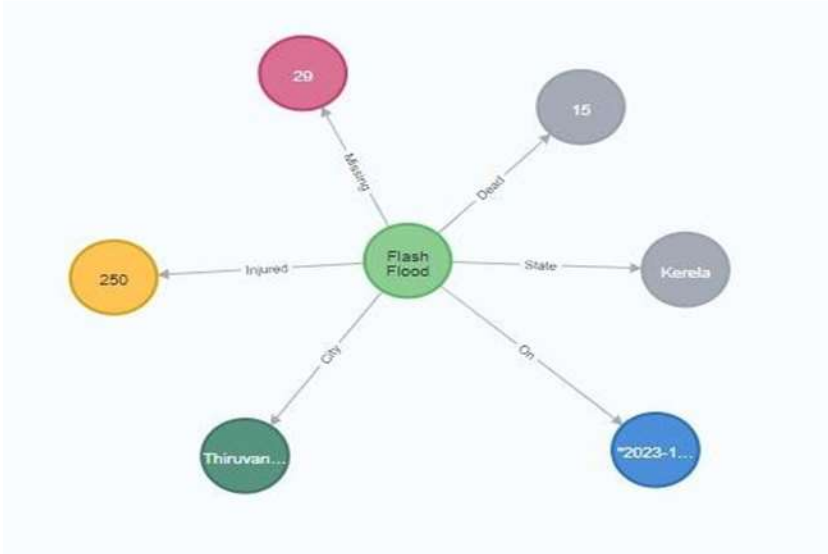

Figure 8. Disaster in Kerala on 18th October 2023

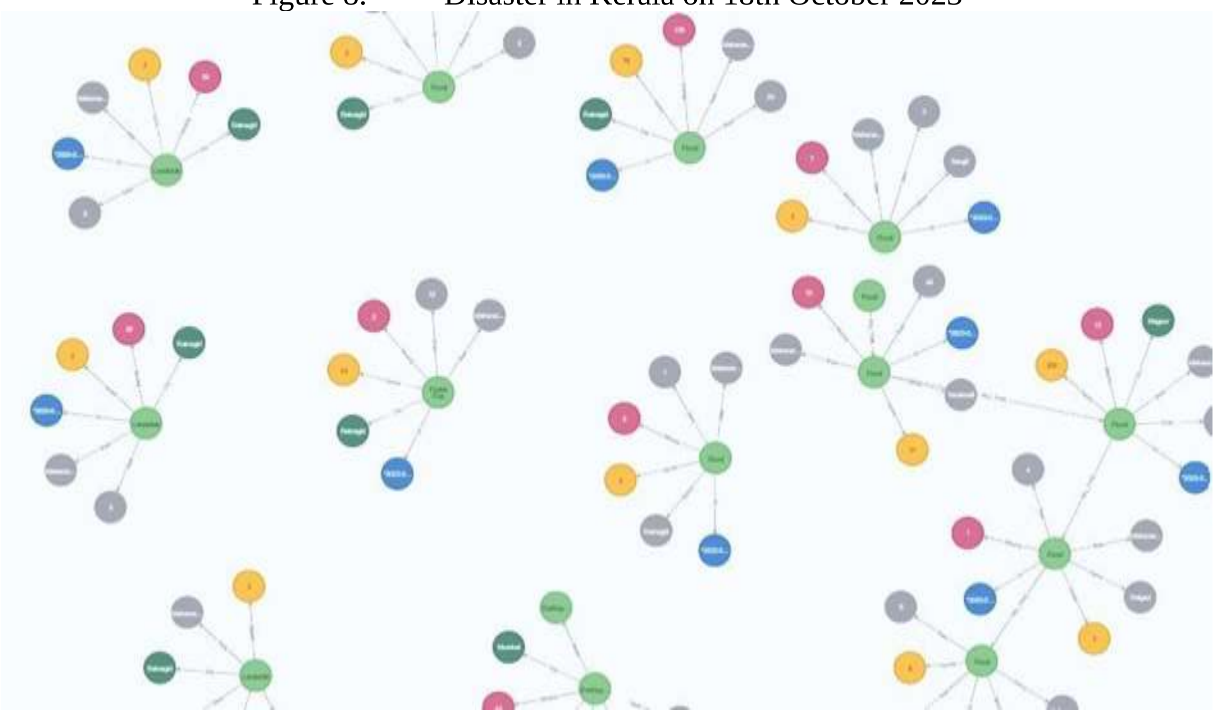

Figure 9. Disaster in Kerala on 18th October 2023

Using the dashboard, disaster information ranging between a few years can be seen. For instance, the horrible floods of Kashmir in 2014 and Uttarakhand in 2013.

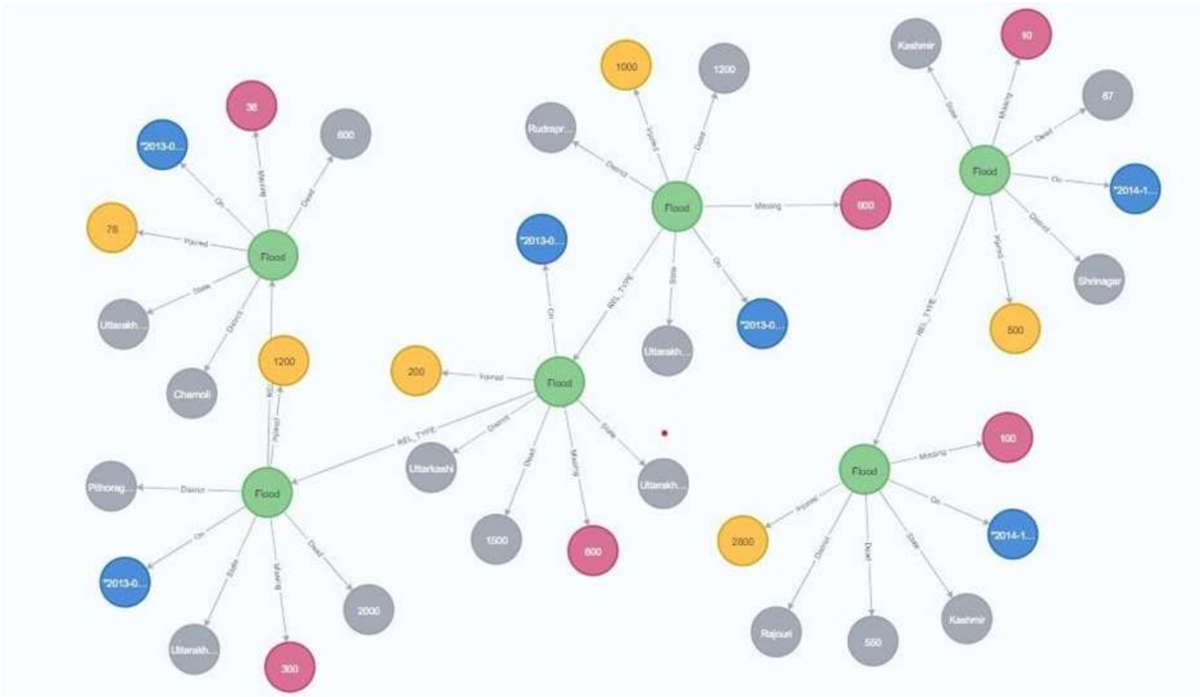

Figure 10. Disasters in Kashmir and Uttarakhand from 2004-2024

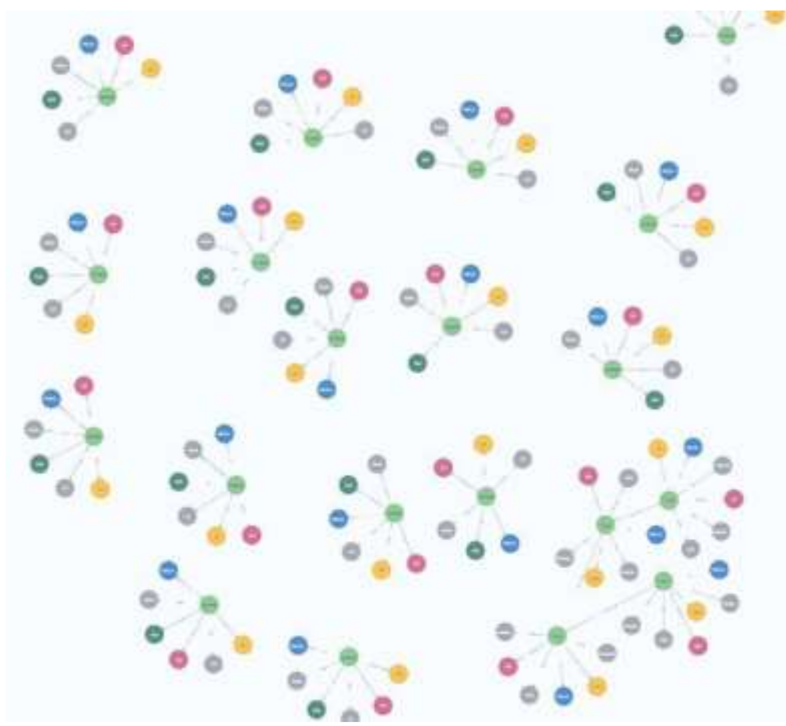

Figure 11. Overview of major disasters in India from 2004-2024

Similarly on a National Scale run the same query, to get all the disasters of India for the year 2024.

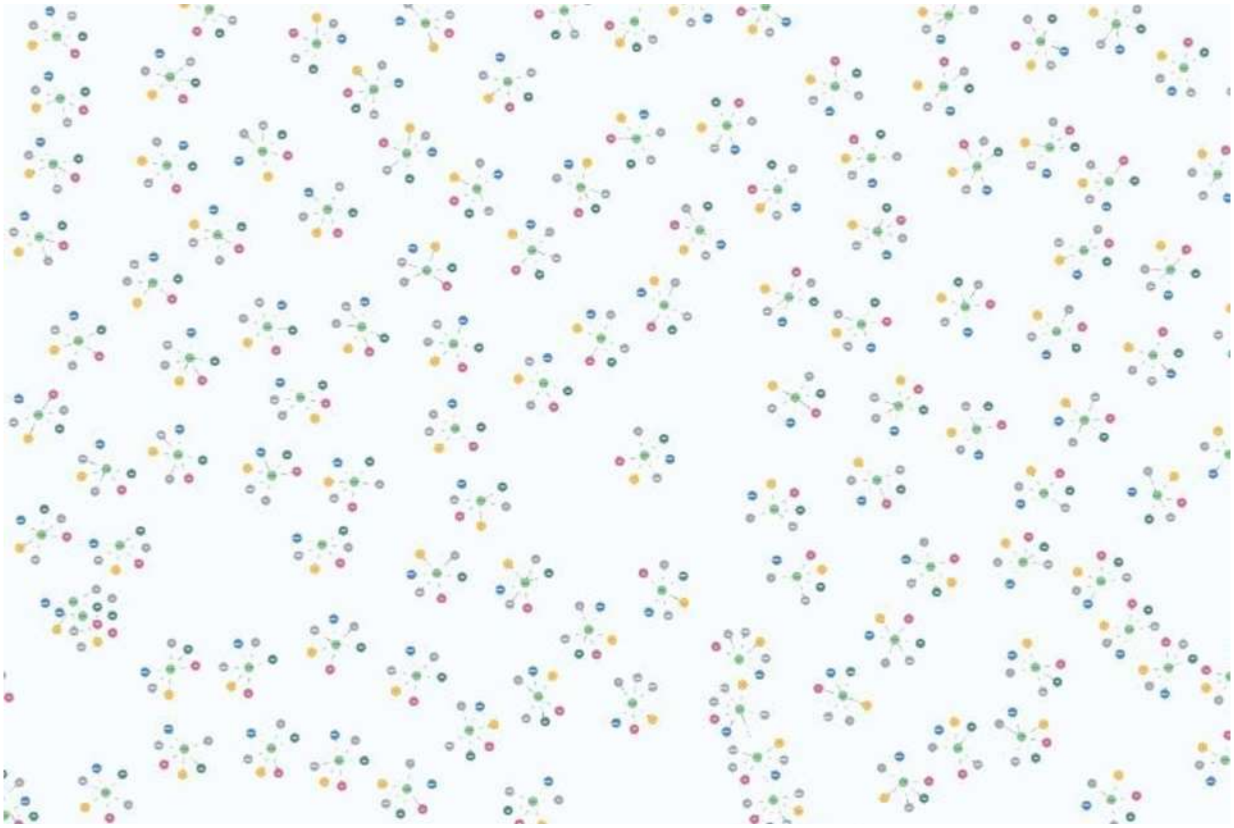

Figure 12. Disasters in India in 2023

Acknowledgements

Grant and fund providers should be acknowledged.

References

Agarwal, M., et al. (2020). Memis: Multimodal emergency management information system. *Advances in Information Retrieval: 42nd European Conference on IR Research, ECIR 2020*, 42, 14-17. https://doi.org/10.1007/978-3-030-45442-5_25

Alam, F., Ofli, F., & Imran, M. (2018). CrisisMMD: multimodal Twitter datasets from natural disasters. *CoRR, abs/1805.00713*. http://arxiv.org/abs/1805.00713

Bisht, D., Singh, R., Gehlot, A., Akram, S., Singh, A., Montero, E. C., Priyadarshi, N., & Twala, B. (2022). Imperative role of integrating digitalization in the firms' finance: A technological perspective. *Electronics, 11*(19), 3252. https://doi.org/10.3390/electronics11193252

Boné, J., Dias, M., Ferreira, J. C., & Ribeiro, R. (2020). DisKnow: A social-driven disaster support knowledge extraction system. *Applied Sciences, 10*(17), 6083. https://doi.org/10.3390/app10176083

Fang, S., Xu, L., Zhu, Y., Ahati, J., Pei, H., Yan, J., & Liu, Z. (2014). An integrated system for regional environmental monitoring and management based on Internet of Things. *IEEE Transactions on Industrial Informatics, 10*, 1596-1605. https://doi.org/10.1109/TII.2014.2302638

Kamoji, S., & Kalla, M. (2023). Effective flood prediction model based on Twitter text and image analysis using BMLP

Kankanamge, N., Yigitcanlar, T., Goonetilleke, A., & Kamruzzaman, M. (2020). Determining disaster severity through social media analysis: Testing the methodology with South East Queensland Flood tweets. *International Journal of Disaster Risk Reduction, 42*, 101360. https://doi.org/10.1016/j.ijdrr.2019.101360

Khajwal, A., Cheng, C., & Noshadravan, A. (2022). Multi-view deep learning for reliable post-disaster damage classification. *ArXiv, abs/2208.03419*. https://doi.org/10.48550/arXiv.2208.03419

Khattar, A., & Quadri, S. M. K. (2022). CAMM: Cross-Attention Multimodal Classification of Disaster-Related Tweets. *IEEE Access, 10*, 92889-92902. https://doi.org/10.1109/ACCESS.2022.3202380

Lwin, K., Sekimoto, Y., Takeuchi, W., & Zettsu, K. (2019). City geospatial dashboard: IoT and big data analytics for geospatial solutions provider in disaster management. *2019 International Conference on Information and Communication Technologies for Disaster Management (ICT-DM)*, 1-4. https://doi.org/10.1109/ICT-DM47966.2019.9032921

Mohanty, S., Biggers, B., SayedAhmed, S., Pourebrahim, N., Goldstein, E., Bunch, R., Chi, G., Sadri, F., McCoy, T., & Cosby, A. (2021). A multi-modal approach towards mining social media data during natural disasters - A case study of Hurricane Irma. *International Journal of Disaster Risk Reduction*, 102032. https://doi.org/10.1016/j.ijdrr.2020.102032

Muhammad, K., Rodrigues, J., Kozlov, S., Piccialli, F., & Albuquerque, V. (2020). Energy-efficient monitoring of fire scenes for intelligent networks. *IEEE Network, 34*, 108-115. https://doi.org/10.1109/MNET.011.1900257

Pathan, A. (2020). Urgent health challenges for the next decade 2030: World Health Organization. *Global Health Journal, 113-117*. https://doi.org/10.37881/1.512

Priyanka, E., & Thangavel, S. (2020). Influence of Internet of Things (IoT) in association of data mining towards the development of smart cities - A review analysis. *Journal of Engineering Science and Technology Review, 13*, 1-21. https://doi.org/10.25103/jestr.134.01

Ren, L., Liu, Y., Wang, X., Lu, J., & Deen, M. (2021). Cloud–edge-based lightweight temporal convolutional networks for remaining useful life prediction in IIoT. *IEEE Internet of Things Journal, 8*, 12578-12587. https://doi.org/10.1109/JIOT.2020.3008170

Salh, A., Audah, L., Shah, N., Alhammadi, A., Qazwan, A. A., Kim, Y., Al-Gailani, S. A., Hamzah, S., Esmail, B., & Almohammedi, A. A. (2021). A survey on deep learning for ultrareliable and low-latency communications challenges on 6G wireless systems. *IEEE Access*, *9*, 55098-55131. https://doi.org/10.1109/ACCESS.2021.3069707

Shah, S. A., Seker, D., Hameed, S., & Draheim, D. (2019). The rising role of big data analytics and IoT in disaster management: Recent advances, taxonomy and prospects. *IEEE Access*, *7*, 54595-54614. https://doi.org/10.1109/ACCESS.2019.2913340

Shah, S. A., Seker, D., Rathore, M., Hameed, S., Yahia, S. B., & Draheim, D. (2019). Towards disaster resilient smart cities: Can Internet of Things and big data analytics be the game changers? *IEEE Access, 7*, 91885-91903. https://doi.org/10.1109/ACCESS.2019.2928233

Sishodia, R., Ray, R., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. *Remote Sensing, 12*, 3136. https://doi.org/10.3390/rs12193136

Son, J., Lim, C.-S., Shim, H.-S., & Kang, J.-S. (2021). Development of knowledge graph for data management related to flooding disasters using open data. *Future Internet*, *13*(5), 124. https://doi.org/10.3390/fi13050124

Sreenivasulu, M., Muthukumarasamy, S., & Jayadev, P. (2021). Multi-modal classification of Twitter data during disasters for humanitarian response. *Journal of Ambient Intelligence and Humanized Computing*, *12*, 10223-10237. https://doi.org/10.1007/s12652-020-02791-5

Sreenivasulu, M., & Sridevi, M. (2021). A novel method for identifying the damage assessment tweets during disaster. *Future Generation Computer Systems*, *116*, 440-454. https://doi.org/10.1016/j.future.2020.10.037

Sufi, F. K. (2022). AI-SocialDisaster: An AI-based software for identifying and analyzing natural disasters from social media. *Software Impacts*, *12*, 100319. https://doi.org/10.1016/j.simpa.2022.100319

Sun, A., & Scanlon, B. (2019). How can big data and machine learning benefit environment and water management: A survey of methods, applications, and future directions. *Environmental Research Letters*, *14*. https://doi.org/10.1088/1748-9326/ab1b7d

Zhang, Y., Zhu, J., Zhu, Q., Xie, Y., Li, W., Fu, L., Zhang, J., & Tan, J. (2020). The construction of personalized virtual landslide disaster environments based on knowledge graphs and deep neural networks. *International Journal of Digital Earth*, *13*(12), 1637-1655. https://doi.org/10.1080/17538947.2020.1773950

Zou, Z., et al. (2021). Disaster image classification by fusing multimodal social media data. *ISPRS International Journal of Geo-Information*, *10*(10), 636. https://doi.org/10.3390/ijgi10100636