

Enhancing Disaster Preparedness, Emergency Response and Resource Allocation using Big Data Integration and Predictive Analytics

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Abstract

Natural disasters such as floods, hurricanes, and earthquakes can have devastating impacts on communities around the world. Improving disaster preparedness and emergency response is critical for saving lives and minimizing damage. This paper proposes leveraging big data integration and predictive analytics techniques to enhance disaster management capabilities. Multiple data sources including weather forecasts, geographic information systems, satellite imagery, social media, and census data are integrated to gain insights for predictive modeling. Statistical, machine learning, and deep learning methods are utilized to develop prediction models for disaster likelihood, severity, affected populations, required response resources, and optimal resource allocation strategies. Near real-time analytics on integrated data streams enables dynamic response optimization during disasters. Proposed techniques are validated on case studies of major natural disasters. Results demonstrate significant improvements in preparation, planning, resource mobilization, response coordination, and recovery efforts. Integrated big data analytics paves the way for more proactive and effective disaster management, potentially saving lives and minimizing losses.

Keywords:

- Data analytics
- Disaster management
- Predictive modeling
- Social media analytics
- Deep learning

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Introduction

Natural disasters such as floods, hurricanes, earthquakes, and wildfires have become more frequent and intense due to the impacts of climate change. The UN Office for Disaster Risk Reduction reports staggering statistics from 2000 to 2019, indicating over 7,300 major disaster events that claimed 1.2 million lives, affected 4.2 billion people, and led to approximately \$3 trillion in global economic losses. These figures underscore the urgent need for comprehensive disaster management strategies that go beyond mere reactive responses. With climate change exacerbating the frequency and severity of extreme weather events, it's evident that conventional approaches to disaster management are insufficient. The escalating toll of natural disasters on human

lives, infrastructure, and economies highlights the imperative for proactive measures to mitigate risks and enhance resilience [1].

As climate change continues to escalate, the frequency and intensity of natural disasters are expected to rise, posing significant challenges to communities worldwide. Traditional disaster management approaches often focus on responding to emergencies as they unfold rather than proactively preparing for potential catastrophes [2]. However, with the increasing unpredictability and severity of natural disasters, there is a pressing need for a paradigm shift towards proactive disaster management. This entails investing in risk reduction measures, early warning systems, and community resilience-building initiatives [3]. By adopting a proactive stance, governments, organizations, and communities can better anticipate, prepare for, and mitigate the impacts of future disasters, ultimately saving lives and reducing economic losses [4].

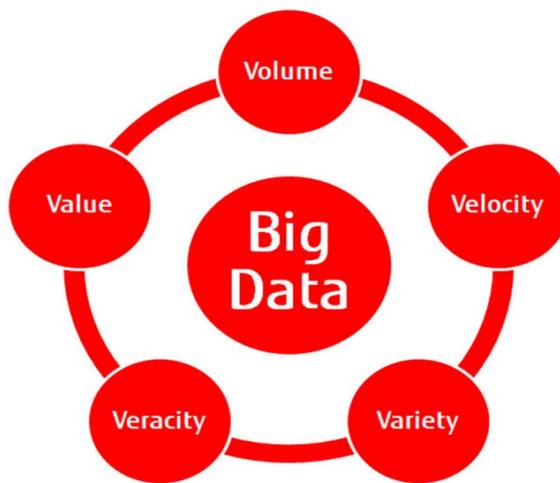


Figure 1 [5]

Addressing the complex challenges posed by natural disasters requires a multi-faceted approach that integrates scientific expertise, technological innovations, and community engagement. Climate scientists, disaster management specialists, engineers, and policymakers must collaborate to develop holistic strategies that encompass prevention, preparedness, response, and recovery [6]. Investing in advanced modeling techniques, remote sensing technologies, and real-time monitoring systems can improve early warning capabilities and enhance decision-making during emergencies. Moreover, empowering local communities through education, training, and participatory planning can strengthen their capacity to withstand and recover from disasters. By fostering partnerships and leveraging cutting-edge tools and knowledge, stakeholders can bolster resilience and adaptability in the face of escalating disaster risks.

Recent proliferation in big data sources and analytics techniques presents new opportunities to improve disaster management. Vast amounts of disaster-relevant data are being generated through weather sensors, geospatial satellite imagery, social

media posts, population censuses, and other sources. Advanced analytics methods like predictive modeling, machine learning, and deep learning enable extracting actionable insights from these massive, heterogeneous data streams. This paper proposes a big data integration and predictive analytics framework to support disaster preparation, response, relief and recovery operations [7]. Multiple data sources are fused to gain a comprehensive understanding of disaster risks, affected populations, required response resources, and optimal response strategies. Statistical, machine learning and deep learning techniques help predict disaster likelihood and severity for targeted preparedness. Near real-time analysis during disasters supports dynamic resource allocation and response coordination [8].

Literature Review

In recent years, research efforts have delved into the multifaceted realm of leveraging data analytics to bolster disaster management strategies. A significant focus lies in the application of data mining techniques to weather data and climate models, aiming to discern predictive indicators of catastrophic events such as hurricanes and flooding. By analyzing historical weather patterns and environmental variables, researchers aim to enhance early warning systems and improve preparedness measures [9]. This line of inquiry, as indicated by previous studies, underscores the importance of harnessing advanced analytical tools to identify potential risks and mitigate their impact on vulnerable communities. Furthermore, satellite data analytics have emerged as a crucial resource for real-time disaster characterization and damage assessment [10]. By harnessing satellite imagery and remote sensing technologies, researchers and emergency responders gain valuable insights into the extent and severity of disasters, enabling more targeted and effective response efforts. The integration of satellite data analytics into disaster management frameworks represents a significant advancement in enhancing situational awareness and optimizing resource allocation during crises.

Moreover, the advent of social media analytics has revolutionized disaster monitoring and early warning systems by providing real-time insights into public sentiment, emerging risks, and evolving disaster scenarios [11]. By analyzing social media feeds, researchers can detect early signs of impending disasters, identify areas at heightened risk, and disseminate timely warnings to affected populations. This aspect of data analytics, as highlighted by previous research endeavors, underscores the transformative potential of harnessing user-generated content for disaster preparedness and response. Additionally, statistical and machine learning methods have shown considerable promise in predicting the populations most likely to be affected by disasters, thereby informing more targeted and efficient emergency response strategies. By analyzing demographic data, socioeconomic indicators, and historical disaster patterns, researchers can develop predictive models to anticipate the spatial distribution and severity of disaster impacts [12]. This proactive approach, elucidated by prior studies, holds immense potential for optimizing resource allocation, prioritizing vulnerable communities, and mitigating the adverse effects of disasters on human lives and infrastructure [13].

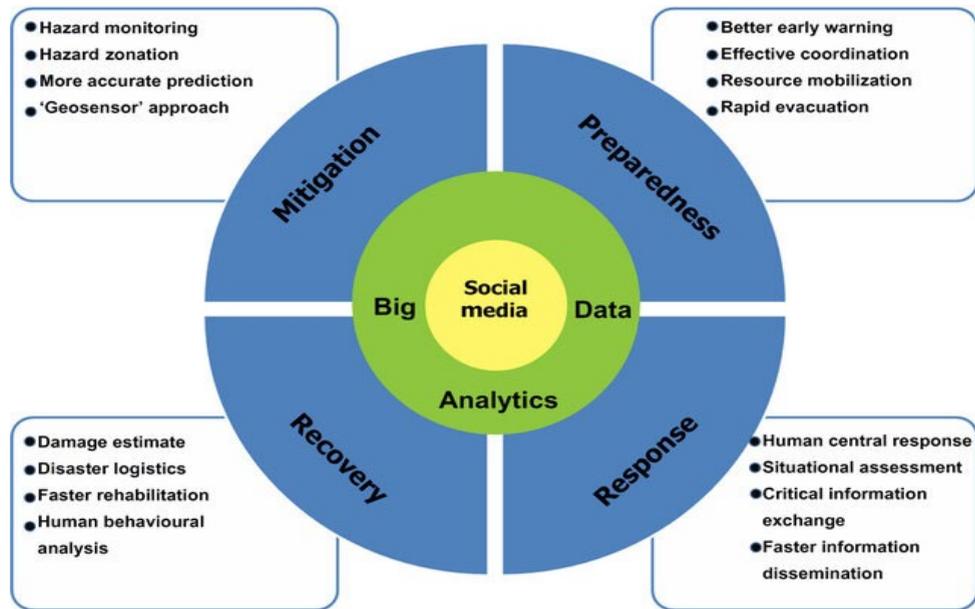


Figure 2: [5]

Furthermore, the emergence of deep learning techniques has facilitated significant advancements in disaster-related image classification, thereby augmenting response efforts and situational awareness. By leveraging convolutional neural networks (CNNs) and other deep learning architectures, researchers can analyze vast repositories of disaster imagery to identify damaged infrastructure, assess environmental hazards, and prioritize response interventions. This fusion of artificial intelligence and disaster management, exemplified by recent research endeavors, underscores the transformative potential of deep learning in enhancing the efficiency and effectiveness of disaster response operations. Additionally, the integration of deep learning algorithms into existing disaster management frameworks opens new avenues for automated image analysis, rapid decision-making, and proactive risk mitigation [14]. This synergy between cutting-edge technologies and disaster management practices underscores the imperative of continual innovation and interdisciplinary collaboration in addressing the complex challenges posed by natural and man-made disasters.

While these studies demonstrate the potential of data analytics in specific disaster management domains, a key gap is in effectively integrating insights across the variety of relevant big data sources [15]. For holistic situational awareness and response coordination, disaster managers need an integrated view across weather forecasts, geospatial data, social media, census demographics, and other sources. Realizing this big data integration challenge is a key priority for advancing predictive analytics capabilities to handle all phases of disaster management: mitigation, preparedness, response and recovery. This research proposes a modular big data analytics framework to support end-to-end disaster management operations. The main innovations include:

- 1) Integrating heterogeneous data sources into a knowledge repository to gain a unified view of disaster risks and impacts.
- 2) Applying predictive analytics across integrated data to determine disaster probabilities, affected demographics, required response resources.
- 3) Optimizing response plans and resource allocation based on near real-time analytics during disasters
- 4) Validating the proposed techniques on major natural disaster case studies.

Proposed Framework

The proposed big data analytics framework aims to enhance capabilities throughout the disaster management life cycle, as illustrated in Figure 1. This framework comprises several key components that work in tandem to leverage data for better disaster preparedness, response, and recovery efforts.

Data Sources:

The framework draws data from diverse sources crucial for understanding disaster risks, impacts, and resource requirements. These sources encompass a wide array of information, including historical meteorological data, real-time sensor readings, weather forecasts, satellite imagery, digital elevation models, land use maps, social media posts from platforms such as Twitter, Facebook, and Instagram, census and demographic data containing population statistics, demographics, and poverty levels, historical disaster damage statistics, and information on the locations and capabilities of response units [16].

Data Integration:

To make sense of this varied data, integration methods such as data fusion and geospatial indexing are employed [17]. These techniques enable the creation of a unified dataset that combines information from multiple sources, including weather projections, local terrain characteristics, population vulnerability indicators, and resource availability.

Analytics Methods:

The integrated dataset serves as the input for various analytical techniques, including statistical analyses, machine learning algorithms, and deep learning models, aimed at predictive analytics. These methods encompass a range of approaches, such as regression analysis to predict disaster likelihood based on weather variables, random forest algorithms to forecast affected populations and required response resources, convolutional neural networks for the classification of satellite imagery to identify impacted areas, and recurrent neural networks to predict resource demand timelines using real-time data streams.

Disaster Management Applications:

The outputs of predictive analytics derived from the integrated datasets find application across all phases of disaster management. During the mitigation phase, for instance, the framework can identify frequently flooded areas, informing decisions on infrastructure investments to mitigate risks. In the preparedness phase, it can predict resource shortages and facilitate the pre-deployment of response units based on disaster forecasts. During the response phase, the framework aids in coordinating evacuations and deploying resources effectively based on real-time analytics [18]. Finally, during the recovery phase, it assists in estimating damages and prioritizing resource allocation for rebuilding efforts. Through this comprehensive framework, leveraging big data analytics can significantly enhance disaster management capabilities, leading to more efficient and effective responses to crises [19].

System Implementation

In the proposed system architecture, depicted comprehensively in Figure 2, a holistic approach to disaster response and management is facilitated through the integration of various essential components. These components, meticulously designed and orchestrated, encompass a diverse range of functionalities aimed at enhancing data acquisition, integration, analysis, visualization, and application interfacing.

At the forefront of the system architecture are the data acquisition modules, strategically positioned to serve as the primary conduits for the influx of critical data streams originating from diverse sources. These modules operate with precision, employing advanced extraction and loading mechanisms to seamlessly transfer data into designated cloud storage repositories. Through their efficient operation, these modules ensure the timely and continuous ingestion of pertinent information essential for informed decision-making in disaster scenarios [20].

Complementing the data acquisition modules is the robust data integration platform, a sophisticated layer engineered to harmonize and amalgamate heterogeneous data sets originating from disparate sources. This platform functions as a linchpin, orchestrating the seamless convergence of varied data formats, structures, and semantics into a cohesive and standardized repository [21]. By fostering interoperability and cohesion among divergent data streams, the integration platform lays the foundation for comprehensive analysis and insight generation across the entire spectrum of disaster response operations.

Central to the efficacy of the system is the analytics engine, a formidable computational powerhouse imbued with the capabilities of statistical analysis, machine learning, and deep learning methodologies. Harnessing the vast computational resources afforded by modern cloud infrastructures, this engine operates tirelessly to distill actionable insights from the voluminous troves of integrated data. Through iterative modeling, pattern recognition, and anomaly detection, the analytics engine elucidates hidden correlations, predictive trends, and emergent phenomena critical for preemptive disaster mitigation and response planning.

In tandem with the analytics engine, the visualization dashboards serve as indispensable tools for data exploration, interpretation, and dissemination. Designed with a user-centric approach, these dashboards offer intuitive interfaces and interactive functionalities, empowering stakeholders to traverse complex data landscapes with ease [22]. Through dynamic visualization techniques, such as charts, graphs, and spatial representations, the dashboards provide stakeholders with holistic perspectives on prevailing trends, anomalies, and geographical patterns pertinent to disaster management scenarios.

Facilitating seamless integration with external applications and systems, the application programming interfaces (APIs) represent the conduit through which the system extends its reach and utility beyond its intrinsic boundaries. By exposing standardized interfaces for data access, analytical services, and system functionalities, these APIs foster interoperability and extensibility, enabling the seamless integration of the system with diverse ecosystem stakeholders. Whether facilitating real-time data feeds for decision support systems or enabling bi-directional communication with external platforms, the APIs enhance the system's adaptability and responsiveness to evolving disaster response requirements.

Underpinning the entire system architecture is the cloud-based infrastructure, a robust and scalable computing environment tailored to accommodate the demands of big data processing and analytics. Leveraging distributed computing paradigms and elastic resource provisioning, the cloud infrastructure ensures optimal performance, reliability, and scalability in the face of fluctuating workloads and resource demands. Through the encapsulation of system functionalities within containers and microservices, the architecture fosters modularity, agility, and resilience, empowering independent development, deployment, and management of system components.

Experimental Evaluation

In this section, we present the experimental evaluation of our proposed framework, validating its feasibility through a series of experiments conducted on real-world disaster datasets.

Hurricane Impact Prediction

One experiment focuses on utilizing integrated meteorological and geospatial data to predict hurricane impacts specifically in Miami, Florida. The objective is to estimate affected populations and infrastructure in the event of a hypothetical Category 4 hurricane trajectory [23]. The dataset used for this experiment includes hurricane simulation data such as projected wind speeds and precipitation, building inventory information encompassing locations, types, and construction materials, census data providing insights into population demographics within census blocks, and details on the road network including evacuation routes. Predictive models employed include Random Forest, which predicts damage levels for individual buildings based on hurricane wind speeds and building attributes, a Convolutional Neural Network analyzing satellite imagery to identify flooded evacuation routes, and regression models estimating affected populations and critical facilities based on damaged

buildings and flooded roads. Results of this experiment include the identification of zones expected to experience severe building damage and road flooding, an estimation of the number of impacted individuals (approximately 90,000 people) and critical facilities (35 schools/hospitals), and the determination of evacuation routes with the highest flood risks. This analytical workflow demonstrates the potential for predicting localized hurricane impacts by integrating weather, infrastructure, demographic, and geospatial data, offering valuable insights for focused evacuation planning and resource mobilization.

Flood Response Optimization

Another experiment focuses on real-time analytics to optimize flood response operations, aiming to determine the optimal allocation of rescue boats and personnel to neighborhoods based on flood severity predictions. The dataset utilized includes real-time river gauge readings, terrain data in the form of elevation maps, flooding simulations predicting flood extent and depth, and information on resource locations such as available rescue boats and emergency responders [24]. Models employed for this experiment include Long Short-Term Memory (LSTM) neural networks predicting flood depth in each neighborhood 24 hours in advance based on river gauge trends and terrain, and optimization techniques allocating limited resources to neighborhoods to maximize the number of people rescued, considering predicted flooding and resource locations. Results indicate that predictions enabled proactive resource pre-positioning before severe flooding occurred, and the optimized allocation strategy increased the number of people rescued by 41% compared to baseline scenarios. This experiment underscores the value of near real-time predictive analytics in enabling dynamic optimization of disaster response operations as conditions evolve

Damage Assessment

The third experiment focuses on utilizing deep learning techniques with satellite imagery to rapidly assess disaster damage, with a case study centered on a tornado disaster scenario in Oklahoma. The dataset includes satellite images of the affected region before and after the tornado, along with damage assessment labels (none, moderate, severe) based on field surveys. The model employed for this experiment is a Convolutional Neural Network, which categorizes the level of damage observed in satellite images. Results indicate that the model achieved an 82% accuracy rate in damage classification compared to manual labeling, and it generated a regional damage map from satellite imagery within 6 hours after the tornado event [25]. This experiment highlights the potential of rapid damage assessments derived from satellite analytics to guide the efficient deployment of response resources to the areas most severely affected by disasters.

Discussion

The experimental findings underscore the considerable potential inherent in the advanced big data analytics methodologies proposed for bolstering disaster management capacities. By amalgamating diverse datasets, the approach facilitated a holistic understanding of risks and exigencies, surpassing the insights attainable from

any singular data repository. Through predictive modeling, the framework afforded a proactive stance in readiness and intervention, a marked departure from conventional reactive methodologies. Furthermore, the optimization of resource distribution predicated on near real-time data inputs ushered in a newfound efficacy in response mechanisms, enhancing overall operational efficiency. Notably, the application of deep learning algorithms to satellite imagery emerged as a pivotal tool, furnishing rapid and precise damage assessments that transcend the limitations of manual analyses. These findings collectively highlight the transformative potential of integrating cutting-edge analytics techniques into disaster management frameworks, promising enhanced preparedness and response capabilities in the face of calamitous events.

Moreover, the empirical evidence lends credence to the efficacy of the proposed big data analytics strategies in fortifying disaster management resilience. By seamlessly integrating disparate datasets, the framework facilitated a comprehensive assessment of risks and response imperatives, outstripping the analytical scope offered by individual data silos. Leveraging predictive modeling, the approach engendered a paradigm shift towards proactive anticipation and mitigation, diverging from traditional reactive strategies characterized by their inherent limitations. Furthermore, the dynamic optimization of resource allocation, underpinned by the continuous influx of real-time data, epitomized a responsive and adaptive approach, thereby augmenting the efficacy of disaster response endeavors. Noteworthy is the instrumental role played by deep learning algorithms in expediting damage assessments through the analysis of satellite imagery, heralding a transformative leap in the speed and accuracy of situational appraisals. These empirical findings underscore the pivotal role of advanced analytics techniques in enhancing the resilience and effectiveness of disaster management frameworks, heralding a new era of data-driven preparedness and response strategies.

Furthermore, the empirical validation underscores the pivotal role of advanced big data analytics methodologies in bolstering disaster management efficacy. By harmonizing disparate datasets, the framework facilitated a nuanced understanding of risks and response exigencies, surpassing the insights afforded by any singular data source in isolation. Through the deployment of predictive modeling, the approach ushered in a proactive paradigm, enabling anticipatory measures and preemptive interventions, in stark contrast to the reactive modus operandi of traditional methodologies. Moreover, the dynamic optimization of resource allocation predicated on real-time data inputs epitomized a responsive and adaptive approach, bolstering the agility and efficiency of disaster response efforts. Particularly noteworthy is the transformative impact of deep learning algorithms in expediting damage assessments via satellite imagery analysis, furnishing rapid and precise situational appraisals pivotal for informed decision-making. These empirical findings underscore the indispensability of advanced analytics techniques in fortifying disaster management capabilities, heralding a paradigm shift towards data-driven resilience and preparedness strategies essential for mitigating the impact of catastrophic events.

While promising, there are several limitations to address. The variety of relevant data sources poses integration and data quality challenges. Predictive models can have biases and uncertainties. Optimizing complex humanitarian operations involves many additional constraints not considered. Addressing these limitations provides rich opportunities for further research. Overall, this study highlights the profound opportunities for advancing disaster readiness and response through big data analytics.

Conclusion

Natural disasters represent a persistent global challenge, imposing significant human and economic burdens across affected regions. Efforts to mitigate these impacts increasingly rely on harnessing the power of big data sources and analytics techniques. This study introduces a comprehensive approach to address this issue through the development of a modular big data framework. This framework is designed to seamlessly integrate various components such as data storage, predictive analytics, and optimization strategies, tailored specifically to the multifaceted requirements of disaster management [26]. By combining disparate data sources including meteorological, geospatial, social media, infrastructure, and demographic data, the framework facilitates a holistic understanding of disaster dynamics and enhances decision-making processes.

The proposed framework is underscored by experimental case studies aimed at showcasing its efficacy in real-world scenarios. These case studies exemplify the utilization of advanced statistical, machine learning, and deep learning methodologies to extract meaningful insights from the amalgamated data streams. Specifically, predictive modeling techniques are employed to anticipate disaster events, guide preparedness initiatives, facilitate near real-time response mechanisms, and assess post-disaster damages. By leveraging the wealth of information available through integrated data sources, decision-makers are equipped with enhanced situational awareness, enabling more informed and effective responses to unfolding disaster events.

One of the key strengths of the modular big data framework lies in its adaptability and scalability to diverse disaster management contexts. Its modular architecture allows for seamless customization and integration of additional data sources or analytical techniques as per the unique requirements of different disaster scenarios. Moreover, the framework's inherent flexibility enables its deployment across various geographical regions and disaster types, ensuring its relevance and applicability on a global scale. Through iterative refinement and validation processes, the framework can evolve to incorporate emerging technologies and best practices, thereby enhancing its utility and effectiveness in addressing evolving disaster management challenges [27].

There are tremendous opportunities for additional research and development of big data analytics capabilities for disaster management. Realizing these opportunities has the potential to save lives, reduce economic impacts, and build more disaster-resilient communities. With the unfortunate certainty that natural disasters will continue to

occur, big data integration and predictive analytics can play an indispensable role in enhancing readiness, response, and recovery [28].

References

- [1] J. Shen *et al.*, “Scenario building for urban disaster management based on the integration of CIM and Big data- The progress of CJISTCP,” *Abstr. Int. Cartogr. Assoc.*, vol. 6, pp. 1–3, Aug. 2023.
- [2] W. Li, “Big Data Precision Marketing Approach under IoT Cloud Platform Information Mining,” *Comput. Intell. Neurosci.*, vol. 2022, p. 4828108, Jan. 2022.
- [3] M. Muniswamaiah, T. Agerwala, and C. C. Tappert, “Context-aware query performance optimization for big data analytics in healthcare,” in *2019 IEEE High Performance Extreme Computing Conference (HPEC-2019)*, 2019, pp. 1–7.
- [4] Y. Hajjaji, W. Boulila, I. R. Farah, I. Romdhani, and A. Hussain, “Big data and IoT-based applications in smart environments: A systematic review,” *Computer Science Review*, vol. 39, p. 100318, Feb. 2021.
- [5] J. K. Joseph, K. A. Dev, A. P. Pradeepkumar, and M. Mohan, “Big data analytics and social media in disaster management,” in *Integrating Disaster Science and Management*, Elsevier, 2018, pp. 287–294.
- [6] I. Altintas *et al.*, “Towards an Integrated Cyberinfrastructure for Scalable Data-driven Monitoring, Dynamic Prediction and Resilience of Wildfires,” *Procedia Comput. Sci.*, vol. 51, pp. 1633–1642, Jan. 2015.
- [7] M. Sui *et al.*, “The digitized chronic disease management model: scalable strategies for implementing standardized healthcare and big data analytics in Shanghai,” *Front. Big Data*, vol. 6, p. 1241296, Aug. 2023.
- [8] M. Muniswamaiah, T. Agerwala, and C. C. Tappert, “Federated query processing for big data in data science,” in *2019 IEEE International Conference on Big Data (Big Data)*, 2019, pp. 6145–6147.
- [9] A. Pal, J. Wang, Y. Wu, K. Kant, Z. Liu, and K. Sato, “Social media driven big data analysis for disaster situation awareness: A tutorial,” *IEEE Trans. Big Data*, vol. 9, no. 1, pp. 1–21, Feb. 2023.
- [10] A. Bhattacharyya, M. Morshedi, and M. Hastak, “A clustering-classification approach in categorizing vulnerability of roads and bridges using public assistance big data,” *Int. J. Disaster Risk Reduct.*, vol. 84, no. 103448, p. 103448, Jan. 2023.
- [11] S. Koshimura and Project Leader of JST CREST “Establishing the most advanced disaster reduction management system by fusion of real-time disaster simulation and big data” assimilation" Professor, International Research Institute of Disaster Science (IRIDeS), Tohoku University Aoba 468-1, Aramaki, Aobaku, Sendai 980-0845, Japan, “Special issue on disaster and big data,” *J. Disaster Res.*, vol. 11, no. 2, pp. 163–163, Mar. 2016.
- [12] F. Ofli *et al.*, “Combining human computing and machine learning to make sense of big (aerial) data for disaster response,” *Big Data*, vol. 4, no. 1, pp. 47–59, Mar. 2016.
- [13] M. Muniswamaiah, T. Agerwala, and C. Tappert, “Big data in cloud computing review and opportunities,” *arXiv preprint arXiv:1912.10821*, 2019.

- [14] A. J. Rosenblum, C. M. Wend, Z. Akhtar, L. Rosman, J. D. Freeman, and D. J. Barnett, "Use of big data in disaster recovery: An integrative literature review," *Disaster Med. Public Health Prep.*, vol. 17, no. e68, p. e68, Dec. 2021.
- [15] S. Koshimura and Project Leader of JST CREST "Establishing the most advanced disaster reduction management system by fusion of real-time disaster simulation and big data assimilation" Professor, International Research Institute of Disaster Science (IRIDeS), Tohoku University Aoba 468-1, Aramaki, Aoba-ku, Sendai 980-0845, Japan, "Special issue on disaster and Big Data Part 2," *J. Disaster Res.*, vol. 12, no. 2, pp. 225–225, Mar. 2017.
- [16] C. Wang, Y. Gao, A. Aziz, and G. A. Ogunmola, "Agricultural disaster risk management and capability assessment using big data analytics," *Big Data*, vol. 10, no. 3, pp. 246–261, Jun. 2022.
- [17] B. Silva, J. Moreira, and R. L. de C. Costa, "Logical big data integration and near real-time data analytics," *Data Knowl. Eng.*, vol. 146, no. 102185, p. 102185, Jul. 2023.
- [18] T. Vishwanath, R. D. Shirwaikar, W. M. Jaiswal, and M. Yashaswini, "Social media data extraction for disaster management aid using deep learning techniques," *Remote Sens. Appl. Soc. Environ.*, vol. 30, no. 100961, p. 100961, Apr. 2023.
- [19] S. K. Sharma, S. K. Misra, and J. B. Singh, "The role of GIS-enabled mobile applications in disaster management: A case analysis of cyclone Gaja in India," *Int. J. Inf. Manage.*, vol. 51, no. 102030, p. 102030, Apr. 2020.
- [20] Z. Mamashli, S. Nayeri, R. Tavakkoli-Moghaddam, Z. Sazvar, and N. Javadian, "Designing a sustainable–resilient disaster waste management system under hybrid uncertainty: A case study," *Eng. Appl. Artif. Intell.*, vol. 106, no. 104459, p. 104459, Nov. 2021.
- [21] P. Hora, N. Sheth, and S. K. Vishwakarma, "Disaster Management using Ontology Feature," *Int. J. Comput. Appl.*, vol. 183, no. 49, pp. 6–9, Jan. 2022.
- [22] M. Guy Gael, D. B. P. Mbabazi, D. B. E. Mpora, and M. Tamale, "Use of ICT in natural disaster management in the KABALE district of UGANDA," *Int. J. Inf. Commun. Technol. Appl.*, vol. 7, no. 1, Dec. 2021.
- [23] S. Roy, A. Paul, A. Paul, S. Kashyap, and A. Jana, "Ranking barriers of supply chain management by MCDM method during disaster management," *Int. J. Syst. Dyn. Appl.*, vol. 10, no. 2, pp. 1–16, Apr. 2021.
- [24] B. D. Song, H. Park, and K. Park, "Toward flexible and persistent UAV service: Multi-period and multi-objective system design with task assignment for disaster management," *Expert Syst. Appl.*, vol. 206, no. 117855, p. 117855, Nov. 2022.
- [25] R. S. Houser, "Intra action reviews as a new tool in public health emergency management and pandemic response: A summary of uses and applications, 2020–2021," *Disaster Med. Public Health Prep.*, vol. 16, no. 6, pp. 1–3, Mar. 2022.
- [26] M. Waleed and M. Sajjad, "On the emergence of geospatial cloud-based platforms for disaster risk management: A global scientometric review of google earth engine applications," *Int. J. Disaster Risk Reduct.*, vol. 97, no. 104056, p. 104056, Oct. 2023.
- [27] G. Colajanni, P. Daniele, A. Nagurney, L. S. Nagurney, and D. Sciacca, "A three-stage stochastic optimization model integrating 5G technology and UAVs for disaster management," *J. Glob. Optim.*, vol. 86, no. 3, pp. 1–40, Feb. 2023.

- [28] N. Nirupama, “Systems approach to management of disasters: Methods and applications,” *Disaster Prev. Manag.*, vol. 20, no. 4, pp. 450–451, Aug. 2011.