

Disaster Impact and Human Resilience Predictor Using Real-Time Data Analytics

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Abstract

The Disaster Impact & Human Resilience Predictor is a real-time analytics system designed to evaluate disaster severity and community resilience. It integrates live data from weather sensors, satellite imagery, social media, and historical records to predict impact zones, infrastructure risk, and required resources. Using machine learning models, the system generates a Human Resilience Score based on social, economic, and healthcare indicators, helping authorities understand how well communities can withstand and recover from disasters. The platform provides early warnings and actionable insights through dynamic dashboards, enabling governments and disaster management teams to make timely, data-driven decisions for effective preparedness and response.

Keywords: Real-Time Data Analytics - Disaster Impact Prediction - Human Resilience Assessment - Machine Learning Models - Early Warning Systems

1. Introduction

1.1. Definition of Disaster Impact and Human Resilience

Disaster impact refers to the adverse effects caused by natural or human-made hazards on communities, infrastructure, and the environment. These impacts may include loss of life, injury, property damage, economic disruption, and long-term social or psychological consequences. The severity of disaster impact depends on the intensity of the hazard, the exposure of vulnerable populations, and the existing preparedness and response capacities. Human resilience, on the other hand, represents the ability of individuals, communities, and systems to withstand, adapt to, and recover from disasters [1], [2]. It includes factors such as social strength, economic stability, technological preparedness, healthcare capacity, and community awareness. Resilience is not merely the absence of vulnerability; it is the presence of coping mechanisms, adaptive strategies, and recovery processes that allow communities to bounce back effectively. Together, understanding disaster impact and human resilience provides a comprehensive framework for assessing risk and

planning effective disaster management strategies [3].

1.2. Importance of Predicting Disaster Impact and Human Resilience

Predicting disaster impact and human resilience is critical for minimizing loss and enhancing community safety. Early prediction helps authorities identify high-risk regions, allocate resources efficiently, and plan evacuation strategies before a disaster strikes [4]. It allows governments and emergency teams to assess potential damage to infrastructure, predict resource shortages, and prepare medical and rescue services in advance. Understanding human resilience levels is equally essential, as the capacity of a community to withstand and recover from disasters varies widely based on socioeconomic conditions, healthcare systems, and public awareness. By predicting resilience, planners can identify vulnerable populations requiring additional support. Predictive analysis enables targeted interventions such as strengthening infrastructure, improving community preparedness, and ensuring rapid post-disaster recovery.

Ultimately, predictive systems enhance decision-making, reduce casualties, minimize economic losses, and promote long-term sustainability. They transform disaster management from a reactive approach to a proactive, data-driven strategy [5].

1.3. Overview of Real-Time Data Analytics in Disaster Response

Real-time data analytics plays a transformative role in modern disaster response by enabling immediate collection, processing, and interpretation of large-scale data from various sources. These sources include satellite imagery, weather sensors, IoT devices, social media updates, drone surveillance, and emergency communication networks. By analyzing this continuous data flow, disaster management systems can detect early warning signs, monitor evolving situations, and predict impact zones with high accuracy [6]. Real-time analytics supports rapid decision-making by providing live dashboards, risk maps, and predictive alerts. It helps authorities understand the severity of a disaster, estimate affected populations, and prioritize resource deployment. Machine learning algorithms further enhance accuracy by learning from historical patterns and adapting to new data. This approach significantly improves emergency preparedness, situational awareness, and response coordination. It ensures timely evacuation, reduces casualties, and accelerates rescue operations. Overall, real-time data analytics strengthens the efficiency and effectiveness of disaster management, making communities more resilient and protected.

2. Literature Review

2.1. Previous Studies on Disaster Impact Prediction

Research on disaster impact prediction has rapidly adopted machine learning and deep learning to translate heterogeneous data (satellite imagery, meteorological records, sensor streams) into actionable forecasts. Early work focused on statistical and physical models, but since ~2017 many studies demonstrate that convolutional neural networks and ensemble methods improve detection and intensity estimation for floods, wildfires, and landslides by extracting spatial-temporal patterns from remote sensing and historical loss data. Recent reviews emphasize hybrid pipelines that combine physical-

model outputs with AI to reduce false alarms and improve spatial resolution, and they highlight challenges such as data imbalance, label scarcity, and model interpretability. Practical systems increasingly fuse geospatial, infrastructure, and socioeconomic layers to estimate exposure and likely economic losses, informing resource allocation for preparedness and response.

2.2. Previous Studies on Human Resilience Prediction

Human and community resilience modeling has progressed from qualitative frameworks to quantitative, multi-domain indices that integrate social, economic, health, and built-environment indicators. Systematic reviews and empirical studies show resilience can be modeled as composite scores or dynamic trajectories that predict recovery speed, mortality, and long-term wellbeing after events. Recent work uses longitudinal datasets and causal inference to link social capital, preparedness, and healthcare capacity with post-disaster outcomes; agent-based and system-dynamics models simulate how interventions alter recovery pathways. Several studies underscore that resilience is context dependent — models trained in one region often fail to generalize — motivating transfer-learning approaches and locally calibrated indices. Validation remains a major gap: diverse outcome measures (injuries, time-to-recovery, economic loss) complicate benchmarking across studies.

2.3. Use of Real-Time Data Analytics in Disaster Management

Real-time analytics has become central to modern disaster management by ingesting live feeds from IoT sensors, social media, drones, and satellite platforms to improve situational awareness. Literature reviews document systems that apply natural language processing to social streams for event detection and geolocation, sensor-fusion architectures for rapid flood mapping, and streaming ML models for dynamic resource prioritization. Studies report clear benefits — faster detection, improved targeting of relief, and better capacity planning — while flagging operational challenges: data privacy, noisy social signals, connectivity loss during crises, and the need for robust edge/Cloud architectures. The consensus is that real-time analytics, coupled with visualization

dashboards and decision-support tools, can transform response, but successful deployment requires interoperability standards, resilient telemetry, and procedures for human–AI collaboration.

3. Methodology

3.1. Data Sources for Real-Time Data

Analytics

Real-time data analytics for disaster prediction relies on diverse and continuously updated data streams. Meteorological data from weather stations, radars, and satellites provide information on rainfall, wind speed, temperature, pressure changes, and storm development. IoT sensors placed in rivers, dams, coastal zones, and urban drainage systems monitor water levels, soil moisture, and structural vibrations. Remote sensing platforms, including drones and

high-resolution satellites, offer visual and thermal imagery to detect environmental changes. Social media platforms, emergency call logs, and crowdsourced mobile applications supply human-generated information that helps identify distress signals, damage reports, and emerging risk zones. Historical disaster datasets and GIS layers provide context for training machine learning models. All these sources are integrated into a centralized data pipeline that performs preprocessing, cleaning, noise reduction, and feature extraction. This combination ensures accurate modeling, faster early warnings, and dynamic situational awareness during disaster events (Figure 1).

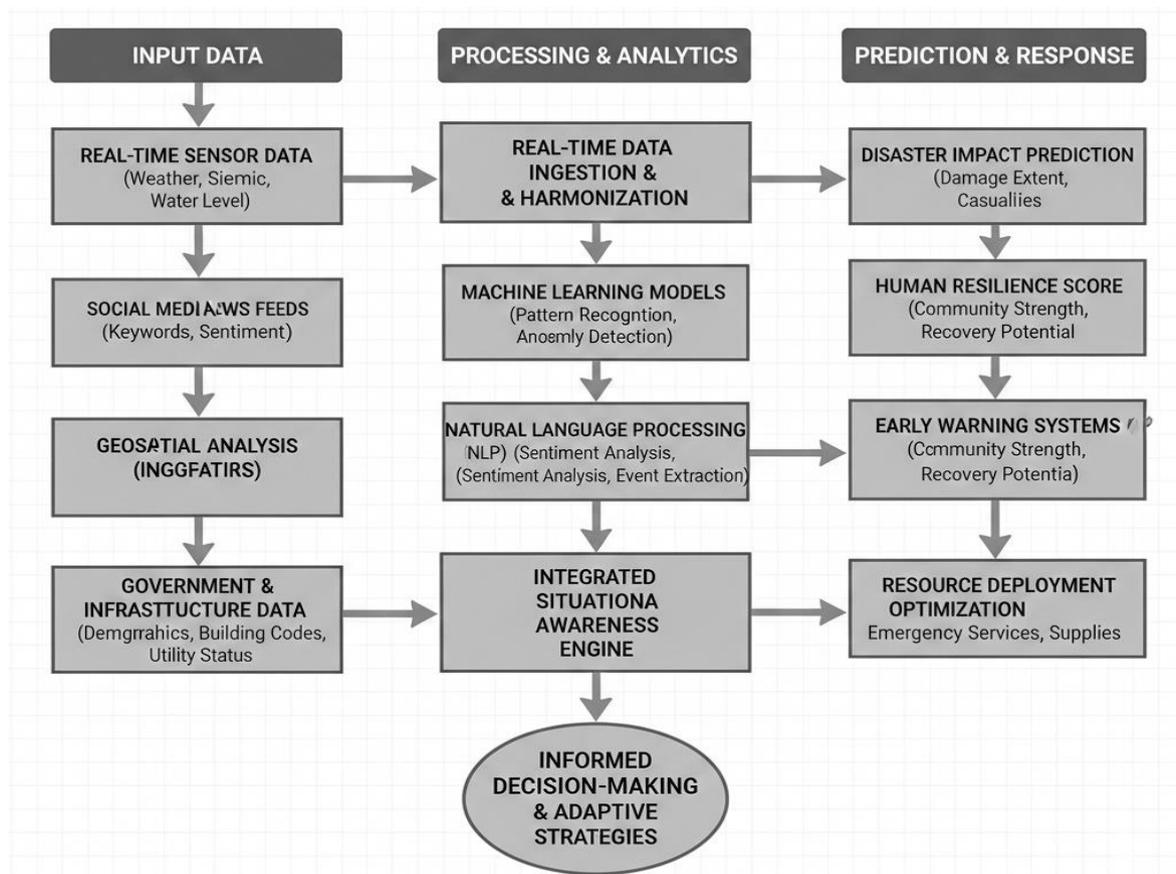


Figure 1 Disaster Impact & Human Resilience Predictor Using Real-Time Data Analytics

3.2. Machine Learning Algorithms for Predicting Disaster Impact

Machine learning algorithms play a crucial role in forecasting disaster intensity, affected areas, and

potential damage. Supervised learning models such as Random Forest, Gradient Boosting, and Support Vector Machines are widely used for classifying risk zones and predicting impact severity. Neural

networks, especially Convolutional Neural Networks (CNNs), analyze satellite images to detect floods, landslides, and storm patterns. Recurrent Neural Networks (RNNs) and LSTM models process time-series data such as rainfall trends and sensor readings to predict disaster progression. Ensemble models combine multiple algorithms to improve accuracy and reduce false alarms. For geospatial predictions, models integrate GIS features, elevation maps, and infrastructure vulnerability scores. After training on labeled historical datasets, the algorithms continuously update with live data inputs, improving their adaptability during real-time events. These predictive systems support emergency teams by providing early warnings, estimating casualties, and identifying zones requiring immediate intervention.

3.3. Factors Influencing Human Resilience in Disaster Situations

Human resilience during disasters is influenced by multiple social, economic, structural, and psychological factors. Socioeconomic status plays a major role, as communities with better income, education, and healthcare access respond and recover more quickly. Infrastructure quality, including housing stability, road connectivity, communication systems, and power supply, contributes significantly to resilience. Health indicators such as physical fitness, chronic illness prevalence, and availability of medical services determine survival and recovery capacity. Social cohesion, community networks, and local leadership also enhance resilience by improving cooperation and access to shared resources. Psychological preparedness, awareness programs, and past disaster experience help individuals make informed decisions during emergencies. Environmental factors, including terrain type and exposure levels, further influence resilience outcomes. By evaluating these indicators, machine learning models can generate a Human Resilience Score, helping authorities identify vulnerable groups and plan targeted interventions before and after a disaster.

4. Results

4.1. Case Studies Demonstrating the Effectiveness of Real-Time Data Analytics in Predicting Disaster Impact

Real-time data analytics has shown high

effectiveness in predicting disaster impact across multiple case studies. During recent flood events in South Asia, real-time sensor data from river basins combined with satellite rainfall estimates enabled authorities to predict overflow zones nearly 6–12 hours before flooding occurred. This early prediction helped initiate evacuation in low-lying areas, significantly reducing casualties. A cyclone case study demonstrated that integrating live meteorological data with machine learning models accurately predicted wind intensity and coastal impact zones, helping disaster management teams pre-position rescue boats, medical supplies, and shelters. Similarly, wildfire monitoring systems in Australia used thermal satellite imagery and wind-speed data to detect fire spread directions in real time, improving firefighter deployment. These case studies highlight that real-time analytics enhances situational awareness, improves lead times for warnings, and supports informed decision-making, demonstrating its strong effectiveness in reducing disaster-related losses.

4.2. Case Studies Showing the Correlation Between Data Analytics and Human Resilience

Several case studies demonstrate a clear correlation between data analytics and improved human resilience. In earthquake-prone regions of Japan, real-time monitoring systems analyze structural vibrations and infrastructure stress levels to assess building safety and inform evacuation decisions. Communities supported by these analytics showed faster recovery and lower injury rates. In hurricane-affected coastal regions of the United States, resilience scoring models that evaluated social vulnerability, healthcare access, and transport connectivity helped identify high-risk populations. Targeted preparedness programs were launched based on these insights, resulting in quicker post-disaster recovery and improved community resilience. In India, flood-prone villages using mobile-based warning apps and crowdsourced data showed higher survival rates and better resource coordination than areas without such digital tools. These cases confirm that when data analytics informs preparedness plans, resource distribution, and community awareness, human resilience

significantly increases, enabling faster adaptation and recovery during disasters.

5. Conclusion

5.1. Summary of Key Findings

This study demonstrates that real-time data analytics significantly enhances the accuracy and effectiveness of disaster impact prediction and human resilience assessment. The integration of meteorological data, IoT sensor readings, satellite imagery, and social media inputs provides a comprehensive and dynamic understanding of evolving disaster conditions. Machine learning algorithms such as Random Forest, Gradient Boosting, CNNs, and LSTMs outperform traditional methods by capturing complex spatial-temporal patterns and delivering more reliable predictions. Case studies reveal that regions using real-time analytics are better prepared, respond faster, and experience fewer casualties and economic losses. Additionally, evaluating human resilience through socioeconomic, health, and infrastructural factors allows authorities to identify vulnerable groups and plan targeted interventions. Overall, the findings show that data-driven systems make disaster management more proactive, accurate, and community-centered.

5.2. Recommendations for Implementing Real-Time Data Analytics in Disaster Response

To fully utilize real-time data analytics in disaster response, governments and disaster management agencies must invest in robust data infrastructure, including IoT sensor networks, resilient communication systems, and interoperable platforms for data sharing. Collaboration between meteorological departments, satellite agencies, emergency services, and research institutions is essential for building integrated data pipelines. Machine learning models must be continuously updated with new data to maintain accuracy, especially during rapidly changing situations. Authorities should implement centralized dashboards that display live risk maps, early warnings, and predictive insights to decision-makers. Training programs for disaster response teams are necessary to improve technical understanding and ensure proper use of analytical tools. At the community level, awareness campaigns and mobile-based reporting

apps can enhance public participation and data collection. By adopting these recommendations, countries can significantly strengthen preparedness, reduce response time, and minimize disaster-related losses.

5.3. Importance of Continued Research in This Area

Continued research in real-time disaster analytics is essential due to the growing frequency and severity of natural disasters driven by climate change. Advanced machine learning models, such as transformers, graph neural networks, and hybrid physical-AI models, hold potential to further improve prediction accuracy.

References

- [1]. Sarker, M. N. I., Peng, Y., Yiran, C., & Shouse, R. C. (2020). Disaster resilience through big data: Way to environmental sustainability. *International journal of disaster risk reduction*, 51, 101769.
- [2]. Cao, L. (2023). AI and data science for smart emergency, crisis and disaster resilience. *International journal of data science and analytics*, 15(3), 231-246.
- [3]. Shah, S. A., Seker, D. Z., Rathore, M. 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.
- [4]. Hao, H., & Wang, Y. (2021). Assessing disaster impact in real time: Data-driven system integrating humans, hazards, and the built environment. *Journal of computing in civil engineering*, 35(5), 04021010.
- [5]. Kumar, V., Mangairkarasi, S., Anitha, J., Priya, V., Yuvasri, B., Nagarajan, S., & Anita, M. (2025). Predictive Analytics for Disaster Management and Urban Resilience: Technologies, Applications, and Future Directions. *Leveraging Urban Computing for Sustainable Urban Development*, 29-54.
- [6]. Sumon, M. F. I., Khan, M. A., & Rahman, A. (2023). Machine Learning for Real-Time Disaster Response and Recovery in the US. *International Journal of Machine*