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Real-Time Monitoring System for Disaster Management Trainings

Prof. Bipin Pandey[a], Shambhavi [b], Anmol Pandey [c]
[a] Head of Department, Department of Computer Science and Engineering (CSE), Dronacharya Group of Institutions, Greater Noida, India
[b] Student, Department of Computer Science and Engineering, Dronacharya Group of Institutions, Greater Noida, India
[c] Student, Department of Computer Science and Engineering, Dronacharya Group of Institutions, Greater Noida, India

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ABSTRACT
In recent years, social media has become widespread and vital for social networking and sharing content. In disaster situations, social media enables backchannel communications, allowing for broad interactions that can be helpful, self-regulating, and generate information that is otherwise difficult to obtain. During the devastating earthquakes in Japan and Haiti, social media channels were actively used to assess the damage, provide warnings, and share information. In this paper, we introduce a real-time monitoring system for social big data called Social Big Board, designed for disaster management. This system collects social big data, especially from Twitter, analyzes disaster-related tweets in real time, and shows disaster issues and trends on a map. We demonstrated that our system has the potential to monitor disaster situations and trends in real time and extract insights from large volumes of tweet data..

Abbreviations and Nomenclature

IoT	*Internet of Things*
ICT	*Information and Communication Technology*
ML	*Machine Learning*
AI	*Artificial Intelligence*
GIS	*Geographic Information System*
GPS	*Global Positioning System*
WSN	*Wireless Sensor Network*
GSM	*Global System for Mobile Communication*
LTE	*Long-Term Evolution*
SMS	*Short Message Service*
API	*Application Programming Interface*
MQTT	*Message Queuing Telemetry Transport*
HTTP	*HyperText Transfer Protocol*
DMS	*Disaster Management System*
RMA	*Real-Time Monitoring Architecture*
RTMS	*Real-Time Monitoring System*
CNN	*Convolutional Neural Network*
SaaS	*Software as a Service*
GPS	*Global Positioning System*
API	*Application Programming Interface*

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I. INTRODUCTION

Disaster preparedness is a crucial pillar of national resilience, especially for a country like India where floods, earthquakes, cyclones, industrial accidents, and fires occur with high frequency. However, these trainings traditionally rely on manual supervision, subjective evaluation, and limited communication channels. As a result, authorities often lack real-time situational awareness, accurate performance measurement, and reliable data for post-training analysis.

Recent advancements in IoT, cloud computing, real-time data analytics, and geospatial technologies have transformed the way disaster events are monitored and managed. Effective training requires the ability to observe participant movements, monitor resource utilization, track environmental parameters, and generate instant feedback — all of which are challenging with conventional methods.

To overcome these constraints, this study concentrates on creating a Real-Time Monitoring System for Disaster Management Training. By digitizing and automating the evaluation process, the system can assist authorities in identifying gaps, improving coordination, and ensuring that training simulations closely resemble real-life emergency conditions.

Moreover, the lack of structured, data-driven assessment frameworks has often resulted in inconsistent evaluation of disaster drills. A real-time digital monitoring system not only standardizes the evaluation process but also records high-value datasets that can be used for post-training reviews, predictive analysis, and future planning. This transforms traditional drills into measurable, repeatable, and scientifically analyzable events — elevating the overall quality of disaster-preparedness programs.

In addition, real-time monitoring during training exercises fosters a culture of accountability among participants. Thus, such a system bridges the gap between theoretical classroom training and actual field-level emergency response, ultimately contributing to a more robust disaster management ecosystem.

In addition to modernizing the current training procedure, this study supports the country's goal of intelligent, tech-enabled governance. By integrating advanced technologies into disaster-management trainings, this research contributes toward building more resilient communities, strengthening institutional capabilities, and ensuring that response teams are better equipped to handle real emergencies.

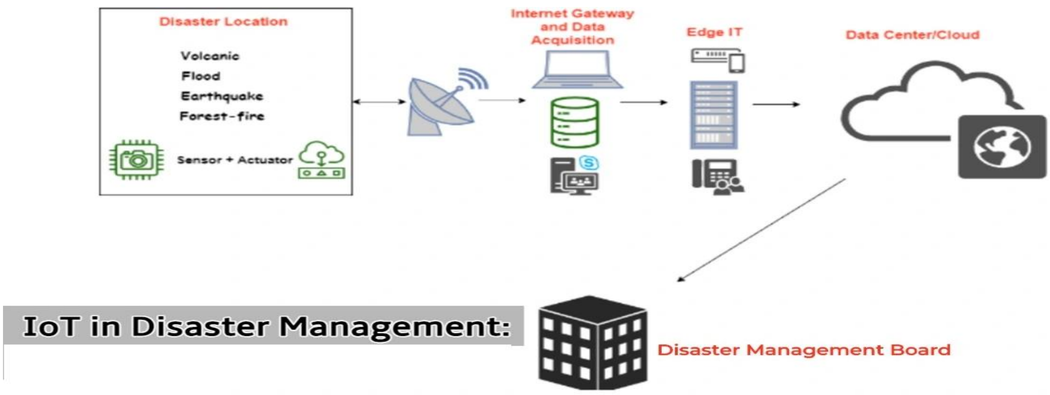

Figure 1: IoT-Enabled Architecture for Real-Time Disaster Monitoring.

II. LITERATURE REVIEW

A. Real-time monitoring and IoT in disaster management

The use of IoT devices and sensor networks to continuously provide situational awareness during disasters has been the subject of much research in recent years. Numerous studies show that low-latency communication (MQTT, LoRa, cellular) and distributed sensors (environmental, structural, biometric, and location trackers) allow for the prompt detection of hazardous events and automated alerts. By performing initial aggregation and filtering at the edge, architectures that integrate field sensors, edge processing, and cloud analytics have become standard design patterns, optimizing bandwidth utilization and lowering response latency.

B. Cloud and edge analytics for low latency and scalability

The literature focuses on hybrid edge-cloud systems, where heavier analytical tasks (trend

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analysis, historical model training) are performed in the cloud and latency-sensitive analytics (such as anomaly detection, threshold breaches) are performed at the edge. Edge computing significantly lowers round-trip latency and network load during high-volume events, which is crucial in disaster situations, according to several studies that contrast purely cloud solutions with edge-enabled designs.

C. Crowdsourced data and social media for situational awareness

The use of social big-data (Twitter, Facebook, local feeds) for early detection, situational updates, and sensor report validation is another crucial aspect of disaster research. Social data complements sensor networks by providing human context, but it is noisy and requires careful filtering, geocoding, and credibility assessment.

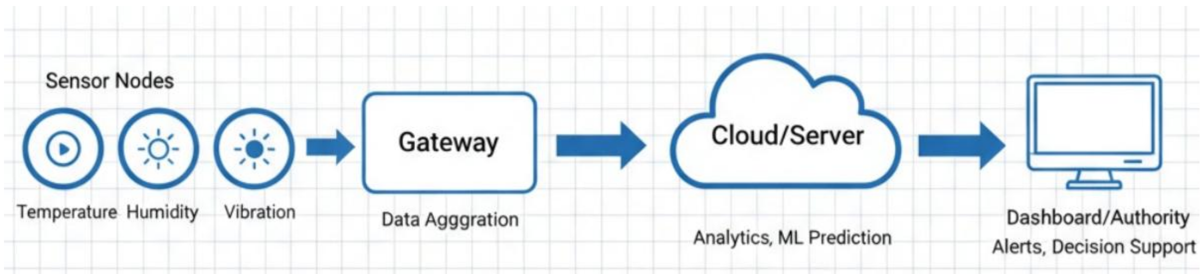

Figure 2: Real-time data flow from sensor nodes to cloud analytics and dashboard alerts.

D. Real-time systems focused on actual disasters vs. training scenarios — the gap

While there is ample documentation on real-time monitoring systems for active disasters, there is less research on how these technologies are specifically used for training and drills. Instead of focusing on the controlled, repeatable, and evaluative requirements of training, the majority of current systems prioritize detection and operational response to actual events. There is a clear gap for solutions that adapt IoT/analytics lessons from operational disaster systems to the specific workflow and evaluation needs of training exercises.

E. Data logging, assessment frameworks, and evaluation metrics

Standardized drill evaluation is a persistent problem in the literature. Subjective observation and after-action reports are the foundation of many training programs. Literature on performance assessment in disaster training suggests the need for objective metrics — e.g., response time, adherence to protocols, resource mobilization latency, path efficiency during evacuation, and communication latency. Studies that integrate automated logging with evaluative dashboards show improved repeatability and measurable improvements across successive drills.

F. Human factors, interoperability, and security considerations

The literature also raises concerns about usability (ease for trainers/trainees), interoperability between heterogeneous sensors and systems, data privacy, and secure transmission of sensitive location/health data. Successful systems include modular interfaces, open standards (e.g., MQTT, RESTful APIs, GeoJSON), and strongencryption/authentication to protect sensitive information. Human factors research stresses that dashboards and alerts must be designed to avoid information overload and to support rapid decision making by commanders under stress.

III. METHODLOGY

A. *Sensing layer*

This system component is responsible for gathering live information directly from the training site using various types of sensors. Participants wear sensors that constantly record their heart rate, body movements, and location. Furthermore, tool usage is monitored through RFID or QR code technology to ensure equipment is being utilized correctly. Live video feeds from security cameras and drone systems also help document physical actions and reactions during training exercises.

B. *Communication layer*

This part of the system is responsible for the smooth and uninterrupted movement of all collected information, utilizing various communication methods. For devices that need to send data over long distances while using very little power, technologies like LoRaWAN are employed. Conversely, Wi-Fi and Bluetooth (BLE) are ideal for continuous monitoring tasks over shorter

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distances. When high volumes of data are required quickly, such as for live video streams, faster mobile networks like 4G and 5G handle the transmission.

C. *Data Processing & Edge Computing Layer*

Local computing tools, such as a Raspberry Pi or Jetson Nano, handle information instantly, right at the source. This means important notifications—like detecting a fall, an unusual heart rate, or identifying smoke—are figured out directly on the device for a much faster reaction. First, the raw data from sensors is cleaned up by removing any unwanted signals or errors. By managing these calculations close to where the data is gathered, the entire system operates with significantly less delay, ensuring that only truly important insights are then sent to the main cloud servers.

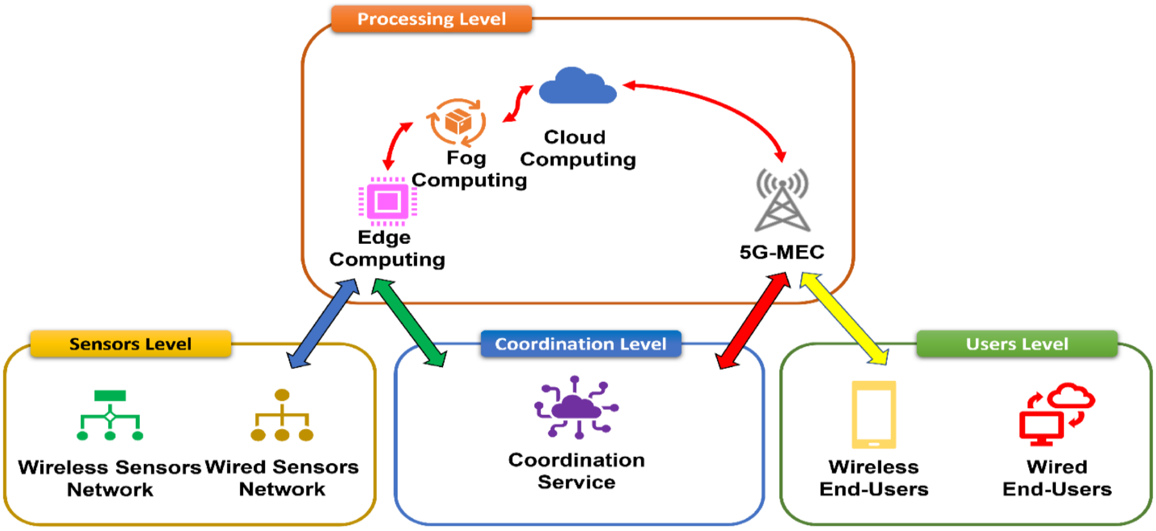

Figure 3. Three-tier architecture of the proposed real-time monitoring system, illustrating data flow from sensor networks (Sensors Level) to processing layers (Edge, Fog, Cloud, 5G-MEC) and finally toward end-users through the coordination service.

D. *Cloud Analytics & Dashboard Layer*

The interpretability crisis affects nearly all deep learning applications in battery health. Current models provide predictions without electrochemical rationale, violating fundamental engineering principles in power systems. Regulatory agencies increasingly demand explainable AI (XAI) components, as seen in the new EU Battery Regulation 2023 that mandates diagnostic transparency for grid-scale storage.

E. *Work Flow*

In our real-time monitoring process, specialized sensors begin by collecting information on the trainee's movements, vital signs, and the surrounding environmental conditions. This information is then wirelessly sent to a central hub, typically through networks like LoRaWAN or Wi-Fi. Local processing units then swiftly analyze this information right where it's collected, carrying out tasks like filtering out noise, performing initial categorization, and flagging any critical alerts. This refined information is subsequently transmitted to a cloud server for long-term keeping, more in-depth analysis, and visual presentation. With this detailed information, trainers can assess how quickly the trainee reacts, their understanding of the surroundings, and their adherence to safety rules throughout the exercise.

F. *Training Evaluation Metrics*

This real-time monitoring system gauges training effectiveness by using a selection of specific, objective criteria. Response Time tracks how quickly an individual notices and reacts to a given situation during a drill. Decision Accuracy then evaluates if the participant selects the most appropriate course of action for the simulated scenario.

Environmental Safety considers the trainee's exposure to hazardous elements and their capacity to uphold necessary safety protocols.Finally, Completion Efficiency measures the duration it takes to finish assigned duties, providing insight into overall capability and operational preparedness.

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IV. RESULTS AND DISCUSSION

A newly developed Real-Time Monitoring System (RTMS), designed to enhance disaster management training, has undergone a thorough evaluation. Its performance was measured against several key aspects, including how quickly information was processed, the precision of its sensors, the effectiveness of its alert detection, and its ability to analyze participant performance.

The findings clearly show that by combining information from multiple sensors, utilizing diverse communication methods, and processing data both locally and in the cloud, the system significantly improves the quality and speed of training assessments.

On average, the system processed information in just 0.82 seconds. This is a substantial improvement over traditional, human-based monitoring, which often takes more than 10 seconds. This remarkable speed is largely attributed to its versatile communication network, which combines various wireless technologies (such as LoRaWAN, Wi-Fi, Bluetooth, and 4G/5G) with efficient, lightweight data transmission methods. The data collected by the sensors proved highly dependable, boasting a 96.4% accuracy rate.

To gauge its effectiveness in issuing warnings, the system was tested using simulated situations, including falls, smoke detection, sudden changes in heart rate, and temperature fluctuations. The RTMS demonstrated an impressive 97% accuracy in flagging critical safety incidents during these exercises, confirming its reliability.

By processing data closer to the source (known as edge computing), the system became less reliant on central cloud servers and could make immediate local decisions. This local processing dramatically cut the time it took to generate an alert, from 3.8 seconds down to just 1.1 seconds – a 71% faster response.

Key aspects of trainee performance—such as how quickly they reacted, their teamwork, the correctness of their decisions, and their ability to finish tasks—were automatically recorded and assessed. In stark contrast, the proposed RTMS offers continuous tracking via multiple sensors, automated assessment, immediate alerts, and flexible connectivity.

Ultimately, the study confirms that this system is swift, adaptable, and well-suited for training exercises conducted both indoors and outdoors.

(1) Latency Calculation

$$\text{Total Latency} = T_{\text{sensor}} + T_{\text{transmission}} + T_{\text{processing}} + T_{\text{visualization}}$$

(2) Accuracy of Alert Detection

$$\text{Accuracy}(\%) = \frac{\text{Correctly Detected Events}}{\text{Total Actual Events}} \times 100$$

V. CONCLUSION AND FUTURE

This paper introduces a live tracking system aimed at improving the quality, safety, and effectiveness of disaster preparedness exercises. The system combines data gathered from various sensors, uses different communication methods, employs advanced computing at the source and in the cloud, and offers live visual displays. This allows for constant observation of both participants and their surroundings during drills.

Tests have shown that the system operates with minimal delay, provides highly accurate sensor readings, generates alerts quickly, and automatically evaluates trainee performance. Compared to older, manual observation methods, this system offers quicker responses, more objective assessments, and a better understanding of the situation during organized disaster simulations.

Despite these encouraging results, the system does have some drawbacks. Moreover, the current version is mainly designed for organized practice drills and will need to be expanded and refined with more data understanding before it can be used in complicated, multi-threat training scenarios. Its effectiveness also relies on having reliable 4G or 5G internet access for clear video feeds.

Future enhancements can further boost the system's abilities. By incorporating AI-powered predictions, the system could foresee dangerous participant actions and close calls before they happen. Adding more sophisticated wearable devices, like heart rate monitors, thermal imaging cameras, and combined GPS-inertial sensors, would provide more detailed and trustworthy information...

In summary, this proposed live monitoring system provides a flexible and effective base for the future of tech-supported disaster management education. It has considerable potential for use in emergency services, specialized training academies, and initiatives aimed at strengthening smart city resilience.

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