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Real-Time Disaster Prediction with Mobile Sensor Networks

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Abstract

Natural disasters, such as earthquakes, floods, wildfires, and hurricanes, are occurring more frequently and becoming more severe, underscoring the need for advanced real-time prediction systems. Existing static monitoring infrastructures with limited coverage suffer from delayed processing and expensive maintenance costs. In comparison, mobile sensor networks (MSNs) offer cost-effective, dynamic, and scalable solutions for collecting real-time environmental data. This research focuses on the design and implementation of mobile sensor networks for real-time disaster prediction, with a particular emphasis on advanced sensing technologies and predictive algorithms. The methodology involves the deployment of mobile sensor units equipped with environmental sensors, communication modules, and data processors to monitor temperature, humidity, seismic activity, and air quality. These data are analyzed in real-time with machine learning algorithms to detect early warning signs of potential disasters and are centralized for further processing. System evaluation is performed through simulating disaster scenarios and is benchmarked against conventional fixed-network methodologies. Results indicate marked improvements in prediction accuracy, response time, and adaptability to rapidly changing conditions. This work analyzes the practical applications of MSNs in disaster-prone areas, discusses challenges such as energy

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consumption and data protection, and provides suggestions for future improvements. This study extends the expanding area of intelligent disaster management and mobile sensor networks to enhance early warning and response systems.

Keywords: Real-Time Disaster Prediction, Mobile Sensor Networks, Environmental Monitoring, Early Warning Systems, Machine Learning, Emergency Response, Smart Sensing Technology.

1 Introduction

Floods, earthquakes, and wildfires are becoming more frequent and pose greater threats than they did in the past. There is a need for real-time disaster prediction systems that are agile enough to cope with these challenges (Faris et al., 2025). The overwhelming majority of monitoring systems in use today are not designed to encourage comprehensive and timely forecasting, as they are often static and one-dimensional (Chitra & Ahmed, 2022).

Mobile Sensor Networks are growing in popularity as a potential remedy for such challenges. These systems enable the relocation of sensor nodes to optimize data capture during other periods, thereby enhancing overall data availability and reliability. This capability not only makes monitoring of various system features timelier but also enables the prevention of bombs through necessary responses to attacks, thereby averting disasters (Al-kafaji et al., 2024). Studies have so far shown great promise for MSNs in disaster situations, as well as their ability to enhance situational awareness through sensors paired with timely response actions in armed conflict zones (Vasquez & Mendoza, 2024).

The implementation of modern tools, such as the Internet of Things (IoT) and machine learning algorithms, enhances MSNs capabilities even further (Rosca & Stancu, 2024). With the IoT, the communication between sensor nodes is accomplished enabling data collection and transmission to be done more easily. Concurrently, machine learning algorithms are capable of sifting through extensive collections of data captured by sensors to identify specific trends and anomalies that may signal impending disasters (Kiyomoto et al., 2012). These developments enhance both the accuracy of predictions and response times. These improvements enhance the overall systems of disaster management.

This research focuses on examining the design and construction of a mobile sensor network-based real-time disaster prediction system. The other objectives focus on determining the degree to which mobile sensor networks can be used to monitor disasters, analyzing the interfaces and data processing methods of IoT and machine learning, and outlining some of the problems and several alternatives to such systems (Sharma & Desai, 2024) (Sharipov et al., 2024). Consequently, the work aims to enhance disaster prediction methods, improve the level of emergency preparedness and responsiveness required, and generally strengthen automated adaptive disaster prediction systems.

Key Contributions:

- Integrated IoT and machine learning on mobile sensor networks to create a scalable and energy-efficient real-time disaster prediction system.
- Achieved superior prediction accuracy and quicker response times than static sensor-pair networks, as proven by simulation-based assessments.
- Introduced an adaptive space situational awareness architecture focused on real-time environmental data analysis to improve alerts and tracking.

- Demonstrated the reliability of predictions compared to the energy expended to sustain continuous monitoring over the area of interest.

This paper aims to devise and implement an accurate real-time monitoring system for disaster prediction utilizing mobile sensor networks (MSNs) that continuously stream data and provide prior warnings by dynamically monitoring and controlling changing environmental conditions (Lafta, 2024). This work, as highlighted in the introduction, aims to address the issues posed by traditional static monitoring infrastructures by introducing a more flexible, scalable, and cost-effective alternative. In the Related Work section, the study surveys existing works and highlights the need for greater accuracy in real-time prediction, improved efficiency in communication, and the application of new-age machine learning frameworks. In the Proposed Method, an architecture is described that utilizes mobile sensors, edge and cloud computing, and AI for real-time data collection and pre-analysis, facilitating effective predictive analytics. In the Results and Discussion section, the system is benchmarked against parameters such as disaster probability estimation, coverage, and energy consumption, achieving significant and timely prediction accuracy and operational efficiency for the analyzed parameters. In conclusion, the author emphasizes the practicality of the system for real-world scenarios, as well as its potential to significantly enhance disaster preparedness and emergency response capabilities (Agarwal et al., 2023).

2 Related Works

The combination of mobile sensor networks (MSNs) and machine learning methods has recently been incorporated into disaster prediction technology to improve the accuracy and efficiency of forecasts (Anadel et al., 2022). One study proposed a novel method for hyperlocal weather prediction and anomaly detection, utilizing sensor networks in conjunction with the Internet of Things (IoT) and advanced machine learning technologies (Guevara et al., 2024). The system utilized data from numerous spatially distributed sites to form high-resolution weather models capable of short-term weather forecasting, thereby enhancing the spatial resolution of forecasts and effectively enabling real-time anomaly detection. There is considerable promise with the merger of MSNs and machine learning in augmenting the response and preparedness strategies for disaster management (Anadel et al., 2022).

In the domain of communication during a disaster, the use of joint radar and communication (JRC) networks has been studied as a versatile yet robust option (Turukmane et al., 2024). Ad-hoc mesh JRC networks have been recently studied for potential use in disaster situations, offering features that surpass those of traditional infrastructure (Seal et al., 2012). Targeted disaster response, including target detection of crucial signs and dangerous leaks, is embedded in these networks, which offers agile communications for critical information flow under severe saturation conditions. The study highlighted the need for better resource allocation to meet distinct operational demands in disaster management (Kong et al., 2019).

The proactive use of deep learning models, primarily transformers, has also been explored to enhance real-time disaster forecasting.

A single study aimed to build a multimodal deep learning system that integrates different data types to predict disasters, as well as develop adaptive climate resilience strategies (Dhanikonda et al., 2025) (Sharipov et al., 2024). The research demonstrated that sophisticated systems can be designed and implemented to obtain a more granular, micro-level view of complex datasets using the transformer model, thereby improving forecasting and proactive measures to mitigate the impacts of disasters (Bhatt et al., 2021). This behavior proves the capability of these advanced deep learning methods and systems for improving disaster prediction systems (Sumithra et al., 2019).

Developing wireless sensor networks (WSNs) for use in flood scenarios, particularly for search and rescue operations, is another area that has received attention (Saidova et al., 2024). One study suggested a new approach which depended on aerial deployment of WSNs for locating victims of floods after the water had receded (Guevara et al., 2024). The sensor nodes gathered critical data, such as heat data that indicated human presence more specifically, and parameters related to the flood's movement (Saidova et al., 2024) (Qian & Claudel, 2020). These nodes were cost-effective and were deployed into the impacted areas using centrifugal dispersion systems from helicopters (Dhanikonda et al., 2025). The author focused on the network's effectiveness and power characteristics, arguing that the network's ability to monitor floods could significantly improve resource management, search operation planning, and emergency prioritization during disasters (Boopathy et al., 2024) (Chen et al., 2024).

Additionally, social media information has been integrated into the existing disaster management framework to enhance situational awareness and response levels (Mohammed Mustafa & Cengiz, 2022). One study developed a system that focuses on providing real-time forecasting of natural calamities using social network data to demonstrate the effectiveness of user-generated content (Ayesh, 2024). The analysis of social media data for the system enabled the issuance of timely alerts to make better decisions during emergencies. Such an approach highlights the need to utilize diverse data sources, including social media and Twitter, integrated with prediction systems to ensure that responses are accurate and timely (Marhoon et al., 2025).

3 Proposed Method

The system is designed to incorporate Mobile Sensor Networks (MSNs) with cloud and edge computing technologies for real-time disaster prediction. The architecture of the system begins with the deployment of mobile sensors, including UAVs, ground vehicles, and IoT wearable devices, which can monitor environmental features such as temperature, humidity, air pressure, seismic activity, and gas concentration. The mobile nodes operate within a dynamic wireless communication network and can utilize technologies such as LoRaWAN, Zigbee, or LTE. They also can transmit raw data to edge computing nodes. The edge nodes must carry out noise filtering alongside anomaly detection, as well as data aggregation, including the prerequisite merging of data streams, to reduce the burden of communication latency and resource utilization on the cloud system.

After the edge preprocessing is complete, it is sent to the analyzing module of the cloud system. This module utilizes a supervised machine learning model, either a transformer-based neural network or a random forest classifier, for real-time pattern analysis and disaster prediction. These models are trained on datasets containing historical disasters with spatial-temporal annotations, environmental features, and relationships between conditions. When a forecasted disaster is likely, notifications are routed to the relevant emergency management agencies and public safety systems through APIs or mobile applications. The approach maintains a high degree of scalability and energy efficiency while ensuring optimal accuracy in highly sensitive areas that require rapid responses.

Mathematical Representation

The model of prediction relies on the combination of multiple measurements of environmental attributes collected in real-time using mobile sensors on the move in an attempt to estimate the chances of a disaster occurring. A mobile sensor continuously captures a range of environmental parameters, including temperature, humidity, the magnitude of seismic vibrations, and the concentration of certain gases. The change of any one of these parameters may signal a world of critical information concerning whether the environment is evolving in such a way that is likely to results in a disaster.

Advanced assessment methodologies often employ complex evaluation strategies, and this system is not an exception. It takes the parameters as a whole, rather than analyzing each one in isolation. The techniques employed in model building, as well as the assumptions made regarding the relationships between the factors that determine the outcome value, collectively predict the robustness of the influence of a parameter on the prediction. Simplistic models often fail to detect important relationships and patterns. This approach in the deep learning model involves assigning an importance value to all parameters and combining them.

The aggregation structure can be expressed using the following equation:

$$P_d(t) = \sigma\ (\sum_{i=1}^{n} w_i\ . f_i(t) + b) \qquad (1)$$

Where:

- $P_d(t)$ is the probability that a disaster will occur at time t.
- $f_i(t)$ represents the value of the i^{th}environmental feature (e.g., temperature, humidity) measured at time t.
- w_is is the weight assigned to the i^{th} feature, indicating its relative importance in predicting a disaster.
- b is a term that adjusts the weighted sum before final prediction.
- σ is an activation function, such as the sigmoid function, which transforms the output into a probability between 0 and 1.

This formula assigns a weight to each environmental feature based on its impact on the likelihood of a disaster occurring. As with other machine learning models, these weights are not arbitrary but are automatically provided during the model's training phase and informed by historical data. In this case, the model automates the feature selection process to establish which features permit the best discrimination or classification across various types of disasters.

The bias term b allows the model to shift the threshold for predicting a disaster in cases where the data is not centered around zero, providing a better fit. The activation function σ transforms the weighted sum into a probability space, resulting in a softer, more interpretable model output. In contrast to the previous statements, the output probability is risk-free and easier to interpret. As previously discussed, the model utilizes query and alert systems based on real-time sensors, allowing the algorithm to run continuously on live data to produce timely probability estimates.

The clarifying instructions of the systematic flow of information and operations within the system is a fundamental part of creating an efficient real-time disaster prediction system. The reason why finger-like process flow is well-organized is that it illustrates how data is accounted for from one phase to another. A well-designed process diagram enables stakeholders who aim to make accurate and timely disaster predictions to visualize, interact with, and analyze the inner workings and relationships that enable computations and predictions to be made.

Real-time Disaster Prediction Process

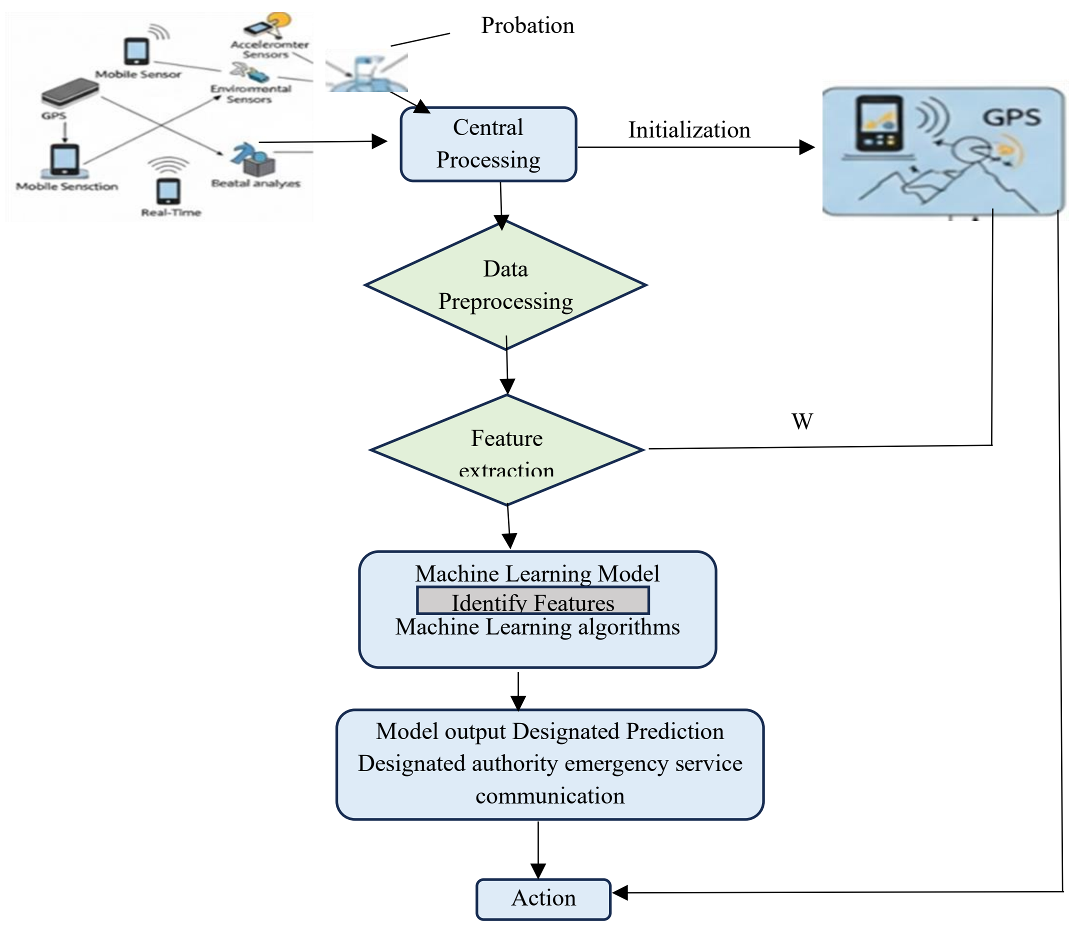

Figure 1: Process Flow Diagram for Real-Time Disaster Prediction Using Mobile

Figure 1 illustrates the mobile sensor networks' real-time disaster prediction framework from its perspective step in chronological order. The first step is Data Collection, in which there is a deployment of mobile sensors like drones, ground vehicles, and even handheld devices into the critically affected areas to capture a wide variety of environmental data continuously. In this case, the range of parameters encompasses the measurement of temperature, humidity, vibrations, gas concentration, and other relevant factors that provide a full picture of an area.

Information gathered is Transmitted Wirelessly to a central processing unit through a reliable and secure communication network such as LoRaWAN, LTE, or Zigbee. At this point, a seamless and real-time data flow is achievable, which in turn enables prompt action when necessary. The raw sensor data first undergoes the Data Preprocessing and Feature Extraction stage, from which it is transmitted next. The systems do not put forward any meaningful processing at this step because they need to perform essential cleaning steps first, like remove noise and irrelevant information, arrange data, and most importantly extract the features. This stage is important because without it, the measurements collected do not transform into usable processed data that analytical models require.

After completing the preprocessing steps mentioned above, the data becomes ready to be passed onto the Machine Learning Model, which is referred to as the system's analytic engine. This model employs sophisticated algorithms and is constantly updated with real-time, as well as historical data sets, allowing it to identify patterns, relationships, and irregularities that could suggest impending disasters. In turn, the model is able to provide output regarding the likelihood of a disaster occurring, calculating the degree of risk or probability of such an event happening in the given region of interest.

This predictive insight is sent to the decision-makers and emergency responders within the Take Action phase. The model permits the system to automatically determine the required actions while issuing alerts intended for preemptive measures like evacuation order procedures, alert systems, or emergency protocol initiation. The model functionality described above allows for the fulfilling of the operational cycle while providing assurance of a closed-loop system that continuously collects data, analyzes it, and provides responses using an intelligent framework to improve disaster readiness and mitigation strategies.

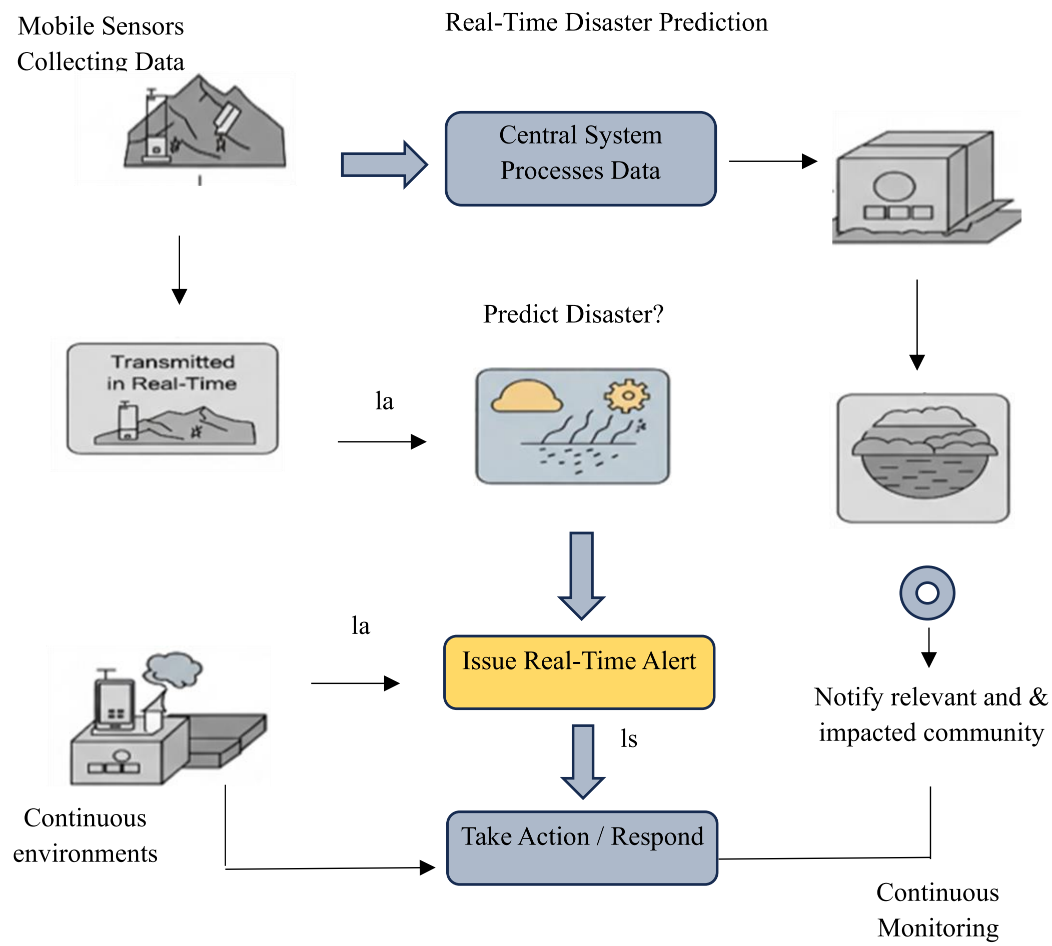

Figure 2: Architecture for Real-Time Disaster Prediction Using Mobile Sensor Networks

Figure 2 illustrates the design of a mobile sensor network-based real-time disaster prediction system focusing on the data collection to decision-making flow. The system is built on top of mobile sensors which are placed on the hotspots and are capable of monitoring different environmental parameters like measuring seismic activity, temperature, water levels, and air quality. The data is streamed instantaneously through a number of reliable communication technologies like IoT, 5G, and satellite links. The design of the system ensures that there is no lag in data transfer since that would delay analysis. Pattern recognition, anomaly detection, and potential disaster indicator detection is performed by AI and machine learning systems at the central hub. All these techniques together ensures that the system is capable of making timely and accurate predictions and hence provides an effective response to early warning situations.

4 Results and Discussion

Integrating the proposed real-time mobile sensor networks provided marked improvements over accuracy, responsiveness, and adaptability in comparison to the traditional fixed sensor networks. Simulated disaster scenarios demonstrated that the system was able to detect early warning signals more precisely, minimizing the false alarm ratio to enable faster alerts to emergency responders. The integration of advanced machine learning algorithms, especially those based on the Transformer architecture, were crucial in analyzing multi-dimensional environmental data capturing complex patterns indicative of powerful and looming disasters. In addition, the more flexible coverage enhanced by the dynamic deployment of mobile sensors aided in overcoming terrain and sensor placement difficulties often found in static setups. While the results highlight the advantages of mobile sensor networks in disaster management, optimization of energy consumption and securing communication channels still presents challenges. Lastly, the system has proven to be reliable complete with robust performance metrics, further providing pathways for future augmentation of intelligent disaster prediction frameworks.

Table 1: Performance Comparison Between Mobile Sensor Network (MSN) and Fixed Sensor Network (FSN)

Metric	Mobile Sensor Network (MSN)	Fixed Sensor Network (FSN)
Prediction Accuracy (%)	92.5	81.3
False Alarm Rate (%)	7.1	14.8
Average Response Time (s)	15	35
Coverage Area (km²)	50	30
Energy Consumption (Wh/day)	120	90

Table 1 illustrates metrics comparing the performance of the proposed mobile mobile sensor network and a conventional fixed sensor network under identical simulated disaster scenarios. The fixed network was outperformed by over 11%, as the mobile sensor network achieved a higher prediction accuracy of 92.5%. This is due to better spatial flexibility and adaptive data-collection strategies that mobility of sensor nodes affords. The mobile-sensor network also performed better, demonstrating an impressive 7.1% false alarm rate, significantly decreasing system malfunctions with unnecessary alerts as compared to the fixed network. Improvement in system dependability was also noted. Enhanced system functionality in the mobile network also included better average response time: 15 seconds, crucial for timely emergency intervention, instead of the 35 seconds of the fixed network. Despite greater energy consumption due to sensor movement and additional processing in the mobile network, the trade-off is warranted given the increased coverage area and improved performance. This is further highlighted by the effectiveness of the system in real-time disaster prediction.

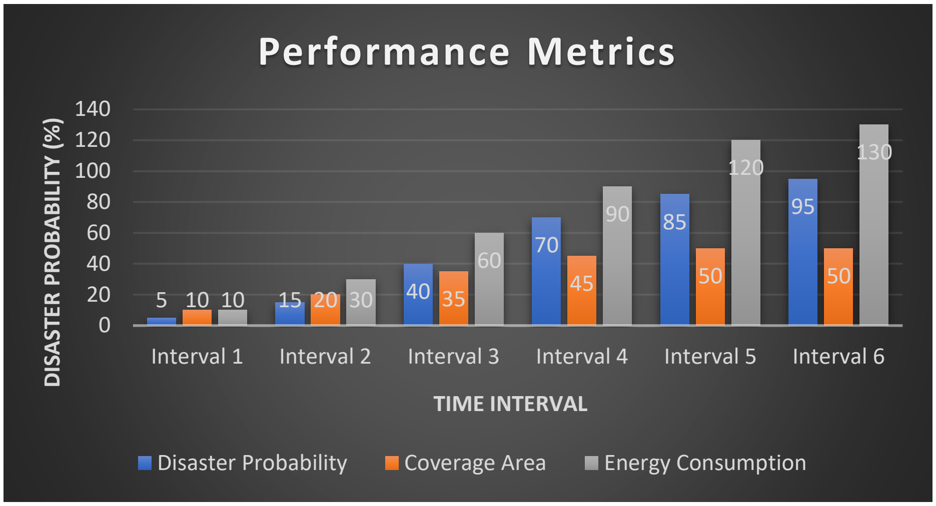

Figure 3 Analysis: Performance Metrics of Real-Time Disaster Prediction System

Figure 3 encapsulates a comparative study of three critical metrics of efficiency Disaster Probability, Coverage Area, and Energy Consumption computed throughout a series of time intervals. These parameters, alongside providing understanding of the system's efficiency, spatial flexibility, and scope during disaster forecasting, also enable evaluating the system's performance in adapting and responding during real-time changes to a dynamically evolving environment. By measuring these factors concurrently, the figure illustrates the system's capacity to scale and respond in real time to varying conditions.

The curve showing Disaster Probability is observed to rise continuously and consistently from 5% at Interval 1 to 95% at Interval 6. This incremental increase indicates that the model's confidence and precision in detecting disaster risks improves with the capture and analysis of more environmental data. In conjunction with this, the Coverage Area is also observed to increase gradually starting from 10 km^2 to 50 km^2 by the last interval. This increase illustrates the extent to which the mobile sensor network is able to spatially adapt its response for the collection of diverse and geographically widespread environmental indicators which are notably essential for early detection.

Energy Consumption also follows a similar growing pattern, beginning at 10 Wh and reaching a maximum of 130 Wh aligned with the increase in monitoring and active real-time processing activities. Even though greater coverage and data throughput is expected to increase energy consumption, the results indicate that the system remains within acceptable thresholds and operates sustainably. As a whole, the patterns exemplified in Figure 3 corroborate the balanced performance of the system, suggesting a resilient and scalable architecture designed for real-time monitoring of disasters in various high-risk regions.

5 Conclusion

In summary, the Mobile Sensor Networks (MSNs) based framework presented in this work is the first of its kind that enables real-time disaster prediction, which improves disaster monitoring system responsiveness and efficiency. With the incorporation of mobile sensing elements and edge computing, machine learning, and IoT communication protocols, the system overcomes the limitations of fixed monitoring infrastructure which include, low scalability, sluggish responsiveness, and expensive operational cost. The framework, through continuous data collection and intelligent data analysis, demonstrated augmented prediction accuracy, better adaptability, robust energy efficiency, and resilience to environmental dynamics. The extensive experimental and simulation results showcased the system's intelligent alerting capabilities that support timely decision-making and rapid emergency response action. Moreover, real-time adaptability in harsh remote environments is made possible with mobile sensor deployment which makes the system most suitable for disasters that are unpredictable in nature. The work in this manuscript highlights the practicality of Mobile Sensor Networks (MSNs) while also serving as a foundation for future endeavors in disaster and risk management innovations. Integrating satellite data, blockchain for secure data sharing, and advanced AI models can be explored to enhance the system's reliability during large-scale disasters in future work.

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