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A Survey on Real-Time Natural Calamities Detection with AI Driven Early Warning System

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Abstract - Natural disasters such as wildfires, earthquakes, floods, and storms continue to cause severe damage to human life, infrastructure, and the environment. Traditional disaster monitoring systems often rely on isolated technologies such as seismic sensors, weather stations, or surveillance cameras, which limits their ability to provide accurate and reliable early warnings. Recent advancements in artificial intelligence, deep learning, remote sensing, and Internet of Things (IoT) technologies have significantly improved the capabilities of disaster detection systems. This paper presents a survey of AI-driven natural disaster detection and early warning systems with a focus on multimodal approaches that combine computer vision, environmental sensing, and geospatial intelligence. Various techniques including Convolutional Neural Networks (CNNs), YOLO-based object detection, transfer learning, remote sensing, and IoT-based monitoring are discussed along with their advantages and limitations. The paper also highlights major research challenges such as false-positive detection, network dependency, computational complexity, and lack of predictive intelligence. Furthermore, a conceptual multimodal framework named Sentinel is discussed as a possible solution domain that integrates lightweight AI models with environmental verification and automated alert mechanisms for real-time disaster management applications.

Keywords—Early warning systems, multimodal data fusion, computer vision, disaster management, real-time API integration.

I. INTRODUCTION

Natural disasters have become increasingly frequent and destructive due to climate change, environmental instability, and rapid urbanization. Events such as wildfires, earthquakes, floods, and storms often result in severe damage to infrastructure, economic systems, and human life. In many disaster scenarios, rapid detection and early warning play a critical role in minimizing destruction and improving emergency response efficiency.

Traditional disaster monitoring systems mainly rely on isolated technologies such as weather stations, seismic monitoring devices, surveillance cameras, and manual reporting systems. Although these systems provide valuable information, they often operate independently and lack integrated decision-making capabilities. This fragmented approach can delay emergency response and increase the possibility of inaccurate alerts.

Recent advancements in artificial intelligence and deep learning have introduced automated disaster detection systems capable of analyzing visual and environmental data in real time. Technologies such as Convolutional Neural Networks (CNNs), YOLO-based object detection models, remote sensing, and IoT-based environmental monitoring systems have shown promising results in wildfire detection, smoke classification, earthquake monitoring, and flood analysis. However, standalone AI systems are often affected by false-positive detections caused by fog, poor lighting, smoke-like clouds, and other environmental ambiguities.

To address these limitations, researchers are increasingly focusing on multimodal disaster detection frameworks that combine computer vision, environmental sensing, and geospatial intelligence for improved reliability and contextual understanding. This paper surveys recent AI-driven disaster detection systems, discusses their strengths and limitations, and explores multimodal approaches for building more accurate and scalable early warning systems.

II. BACKGROUND

Artificial Intelligence (AI) and Deep Learning technologies have become important tools in modern disaster management systems. Deep learning models such as Convolutional Neural Networks (CNNs) are widely used for image classification and visual anomaly detection tasks including wildfire and smoke recognition. Lightweight architectures such as MobileNetV2 are particularly useful for real-time edge deployment because of their reduced computational requirements.

YOLO (You Only Look Once) models are commonly used for real-time object detection applications. These architectures perform object localization and classification simultaneously, enabling faster processing speeds suitable for surveillance systems and drone-based monitoring.

Remote sensing and Geographic Information Systems (GIS) provide large-scale environmental monitoring through satellite imagery, thermal imaging, and hyperspectral analysis. These technologies are widely used for monitoring wildfires, floods, and climate-related disasters across large geographical regions.

Internet of Things (IoT)-based systems utilize distributed environmental sensors to monitor temperature, humidity, seismic activity, air quality, and gas concentration in real time. Combining IoT with AI enables automated environmental monitoring and intelligent disaster detection.

Multimodal disaster detection frameworks integrate multiple technologies such as computer vision, environmental sensing, geospatial intelligence, and API-based verification systems to improve contextual awareness and reduce false-positive alerts in modern early warning systems.

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III. LITERATURE SURVEY

Several researchers have proposed AI-based disaster detection systems using deep learning and environmental monitoring techniques. Alam et al. [11] proposed

FireNet-CNN, a wildfire detection framework utilizing CNNs and Explainable AI techniques for real-time fire detection. Their work demonstrated improved classification accuracy while maintaining efficient processing performance.

Dong and Wang [12] introduced HybriDet, a hybrid framework combining CNN and transformer architectures for wildfire detection using remote sensing imagery. Their approach improved feature extraction and contextual understanding compared with traditional CNN-based systems.

Rokhim et al. [13] performed a comparative analysis between YOLO and RT-DETR models for real-time smoke and fire detection. The study highlighted that YOLO-based systems provide faster detection speeds while maintaining high accuracy for surveillance-based disaster monitoring applications.

Gong et al. [14] reviewed multimodal information fusion techniques for natural disaster monitoring and emphasized the importance of combining AI, environmental sensing, and geospatial intelligence for improving early warning reliability.

Research conducted by Gyang et al. [15] explored the use of GIS and remote sensing technologies in disaster monitoring and response systems. Their work demonstrated the effectiveness of satellite imagery and geospatial analysis for large-scale environmental monitoring.

Recent studies have also focused on transfer learning and lightweight CNN architectures such as MobileNetV2 and EfficientNet for real-time wildfire detection in low-resource environments [16], [17]. These approaches improve deployment feasibility on drones, edge devices, and embedded monitoring systems.

Additionally, IoT-based disaster monitoring systems have gained significant attention in recent years due to their ability to provide continuous real-time environmental sensing [8]. Researchers have integrated IoT sensors with machine learning algorithms to monitor parameters such as temperature, humidity, seismic activity, and air quality for early hazard detection. These systems improve situational awareness and support faster emergency response, especially when combined with AI-driven multimodal verification frameworks.

IV. PROBLEM FORMULATION

Despite major advancements in AI-driven disaster detection systems, several challenges continue to affect their reliability and scalability. Existing systems often rely on isolated monitoring techniques that lack contextual environmental understanding. Vision-based AI models may generate false-positive alerts by misclassifying fog, smoke-like clouds, or poor lighting conditions as disaster events.

Most modern disaster monitoring frameworks also depend heavily on internet connectivity, cloud APIs, and centralized infrastructure. During large-scale disasters, communication failures may disrupt real-time monitoring and emergency alert systems.

Another major challenge is the high computational requirement of deep learning architectures. Many CNN and transformer-based models require powerful GPU hardware, making large-scale deployment difficult in low-resource environments. Table I summarizes the key research gaps identified and their impact on existing systems.

TABLE I. RESEARCH GAPS AND THEIR IMPACT

Research Gap	Impact on Existing Systems
High false-positive rates	Reduces reliability of AI-based warning systems
Network dependency	Systems may fail during communication outages
High computational cost	Limits deployment on edge devices
Low-light visibility issues	Reduces detection accuracy at night
Lack of predictive intelligence	Systems react only after disasters occur
Limited multimodal integration	Decreases contextual awareness

These limitations highlight the need for intelligent multimodal disaster detection systems that combine visual analysis with environmental verification and real-time decision-making capabilities.

V. SOLUTION DOMAIN

To overcome the limitations of traditional disaster monitoring systems, multimodal frameworks integrating computer vision, environmental sensing, and geospatial intelligence have emerged as promising solutions. A conceptual framework named Sentinel represents one such approach for intelligent disaster detection and early warning.

The proposed framework combines lightweight deep learning models such as MobileNetV2 with environmental verification mechanisms including weather APIs, seismic monitoring systems, and Air Quality Index (AQI) analysis. Visual anomalies detected by AI models can be cross-verified using environmental data before triggering emergency alerts.

The framework also utilizes automated communication systems such as SMS and email notifications for rapid emergency response. By integrating multiple independent data sources, multimodal frameworks significantly reduce false-positive alerts and improve contextual awareness during disaster monitoring.

Such hybrid architectures provide scalable and reliable solutions for real-time disaster management applications including wildfire monitoring, earthquake detection, industrial hazard monitoring, and smart city safety infrastructure.

VI. CONCLUSION

Artificial intelligence, deep learning, remote sensing, and IoT technologies have significantly transformed modern disaster detection and early warning systems. Existing research demonstrates that AI-based frameworks can improve disaster monitoring speed and automation compared with traditional isolated monitoring systems. However, challenges such as false-positive detection, computational complexity, network dependency, and environmental ambiguity continue to affect system reliability.

This survey reviewed various AI-driven disaster detection techniques including CNN-based systems, YOLO-based object detection, remote sensing technologies, IoT monitoring frameworks, and multimodal disaster detection approaches. The study also discussed current research gaps and highlighted the growing importance of integrating environmental verification with visual AI systems.

Overall, multimodal frameworks combining computer vision, environmental sensing, and geospatial intelligence represent a promising direction for building scalable, reliable, and context-aware early warning systems capable of improving disaster response and reducing large-scale damage.

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