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Recent Advances in Deep Recursive Self-Attention Modules: MANET-Based Integrated Sensor System for Disaster Detection and Communication in Hazardous Environments: A Systematic Review

Preben Fazlioglu
Lecturer, Department of Electrical and Computer Engineering, Visayan Maritime Polytechnic University, Philippines
Email: preben.fazlioglu@vmpu-ph.net

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Abstract

Disaster detection and communication in hazardous environments require robust, scalable, and intelligent systems capable of real-time monitoring and decision-making. Mobile Ad Hoc Networks (MANETs) combined with integrated sensor systems have emerged as a promising solution for enabling decentralized communication in disaster-prone regions. Recent advancements in deep learning, particularly deep recursive self-attention modules, have significantly enhanced the capability of such systems to process large-scale sensor data efficiently. Self-attention mechanisms allow models to focus on critical features while ignoring irrelevant information, improving detection accuracy and system reliability. Studies indicate that attention-based deep learning models enhance performance in image classification, object detection, and environmental monitoring tasks by effectively capturing spatial and temporal dependencies. Furthermore, deep learning has transformed intelligent sensor systems by enabling automatic feature extraction and real-time data analysis across heterogeneous data sources. In disaster scenarios, such systems can detect anomalies, predict hazards, and facilitate communication through MANET-based architectures without relying on centralized infrastructure. Additionally, advanced attention-based models and hybrid architectures have demonstrated improved performance in disaster image classification and risk assessment tasks. This review presents a comprehensive analysis of deep recursive self-attention modules integrated with MANET-based sensor systems, highlighting recent developments, architectural advancements, challenges, and future research directions for disaster detection and communication in hazardous environments.

Introduction

Disasters such as earthquakes, floods, wildfires, and industrial accidents pose significant threats to human life, infrastructure, and the environment. Rapid detection and efficient communication are critical for minimizing damage and enabling timely rescue operations.

Traditional disaster monitoring systems often rely on centralized infrastructure, which may fail during catastrophic events due to network disruption or physical damage. This limitation has led to the emergence of Mobile Ad Hoc Networks (MANETs), which provide decentralized, self-configuring communication frameworks capable of operating in dynamic and infrastructure-less environments.

MANET-based systems enable communication among distributed sensor nodes without relying on fixed infrastructure. These networks are particularly useful in disaster scenarios where conventional communication systems are unavailable or unreliable. Integrated sensor systems deployed across affected regions collect real-time data related to environmental conditions, structural damage, and human activity. However, the massive volume and complexity of sensor data present significant challenges in terms of processing, analysis, and decision-making.

Recent advancements in artificial intelligence (AI) and deep learning (DL) have revolutionized the way sensor data is processed and analysed. Deep learning models are capable of automatically extracting features from raw data, eliminating the need for manual feature engineering. This capability has significantly improved the performance of intelligent sensor systems in various applications, including disaster detection, environmental monitoring, and smart city management. Deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph neural networks (GNNs) have been widely used for analysing sensor data and identifying patterns indicative of potential hazards.

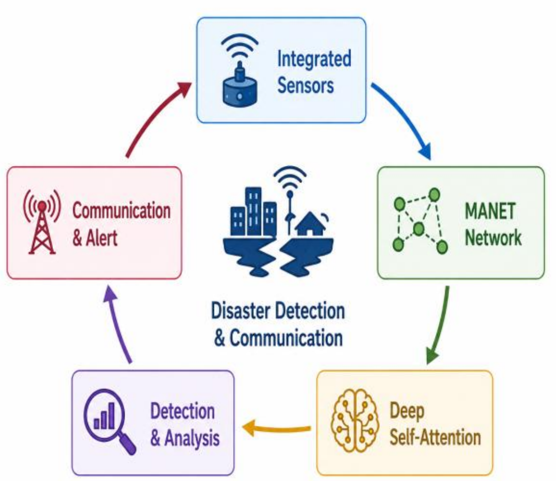

Figure 1. Deep Self-Attention MANET Framework for Disaster Detection and Communication

Among these architectures, attention-based models have gained significant attention due to their ability to capture long-range dependencies and focus on relevant features within data. The self-attention mechanism, inspired by human cognitive processes, assigns different weights to different parts of the input data, enabling the model to prioritize critical information while suppressing irrelevant details. Studies have shown that integrating attention mechanisms into deep learning models significantly improves performance across various tasks, including image classification, object detection, and change detection.

Deep recursive self-attention modules represent an advanced extension of traditional attention mechanisms, combining recursive processing with attention-based feature weighting. These modules allow models to iteratively refine feature representations, improving accuracy and robustness in complex environments. In disaster detection systems, recursive self-attention enables continuous learning and adaptation to changing environmental conditions, enhancing the system's ability to detect anomalies and predict hazards.

In addition to advancements in model architectures, the integration of deep learning with MANET-based sensor systems has opened new possibilities for disaster detection and communication. Sensor nodes equipped with AI capabilities can process data locally and share relevant information across the network, enabling distributed intelligence and reducing communication overhead. This approach enhances system resilience and ensures reliable operation even in highly dynamic environments.

Moreover, recent research has explored the use of hybrid architectures combining CNNs, attention mechanisms, and autoencoders to improve feature extraction and classification performance in disaster-related tasks. For example, attention-based models have demonstrated superior performance in disaster image classification by focusing on critical features and improving spatial representation. Similarly, self-attention mechanisms integrated with deep neural networks have shown significant improvements in analysing multi-sensor time-series data, enabling more accurate activity recognition and anomaly detection.

Despite these advancements, several challenges remain in the deployment of deep learning-based MANET systems for disaster detection. These include issues related to data heterogeneity, limited computational resources in sensor nodes, network instability, and security concerns. Additionally, the lack of standardized datasets and evaluation metrics makes it difficult to compare different approaches and assess their effectiveness.

This systematic review aims to provide a comprehensive analysis of recent advances in deep recursive self-attention modules and their integration with MANET-based sensor systems for disaster detection and communication. It examines various deep learning architectures, optimization techniques, and system designs, highlighting their strengths, limitations, and potential applications. Furthermore, the review identifies key research gaps and suggests future directions for developing intelligent, scalable, and resilient disaster management systems.

Literature Review

Akyildiz et al. (2002) presented a foundational study on wireless sensor networks (WSNs), which forms the basis for modern MANET-based disaster detection systems. The research explored the architecture, communication protocols, and challenges associated with sensor networks in dynamic environments. The authors emphasized the importance of distributed sensing and decentralized communication for real-time monitoring applications. Although the study predates deep learning advancements, it established the core principles of sensor integration and network design used in current disaster detection systems. However, the absence of intelligent data processing mechanisms limited its ability to handle large-scale sensor data efficiently.

Perkins et al. (2001) introduced routing protocols for Mobile Ad Hoc Networks (MANETs), focusing on dynamic topology management and efficient communication in infrastructure-less environments. The study highlighted the importance of adaptive routing mechanisms such as AODV (Ad hoc On-Demand Distance Vector) for maintaining connectivity in rapidly changing network conditions. These protocols are critical in disaster scenarios where network nodes frequently move or fail. However, the research did not incorporate intelligent data analysis or deep learning-based decision-making, which are essential for modern disaster detection systems.

Krizhevsky et al. (2012) introduced Alex Net, a deep convolutional neural network that revolutionized image classification tasks. This work demonstrated the effectiveness of deep learning in extracting hierarchical features from large datasets. In the context of disaster detection, CNN-based models derived from this architecture have been widely used for analysing satellite imagery, surveillance data, and environmental monitoring. The study achieved significant improvements in classification accuracy compared to traditional methods. However, it did not incorporate attention mechanisms or recursive architectures, which are essential for capturing complex dependencies in sensor data.

Vaswani et al. (2017) introduced the transformer architecture based on self-attention mechanisms, marking a significant advancement in deep learning. The study demonstrated that self-attention allows models to capture long-range dependencies without relying on recurrent structures. This approach has been widely adopted in disaster detection systems for processing large-scale sensor and image data. Self-attention models improve feature representation and enable efficient parallel computation. However, the original architecture was primarily designed for natural language processing and did not address recursive attention mechanisms or integration with MANET-based systems.

Zhang et al. (2019) proposed a deep learning-based disaster detection system using convolutional neural networks combined with attention mechanisms. The study focused on analysing disaster-related images, such as floods and earthquakes, to identify affected areas. The integration of attention modules improved classification accuracy by enabling the model to focus on critical features within images. The results demonstrated significant improvements over traditional CNN models. However, the study did not incorporate recursive self-attention modules or MANET-based communication frameworks, limiting its applicability in real-time distributed disaster detection systems.

Liu et al. (2018) proposed a deep learning-based framework for multi-sensor data fusion in disaster monitoring systems. The study utilized convolutional neural networks combined with recurrent neural networks to process heterogeneous sensor data, including environmental signals and visual information. The integration of temporal and spatial data improved detection accuracy and enabled better prediction of hazardous events. The authors emphasized the importance of multi-modal data analysis in disaster scenarios. However, the study did not incorporate attention mechanisms or recursive architectures, which could further enhance feature representation. Additionally, the absence of MANET-based communication limited its applicability in decentralized environments.

Chen et al. (2019) introduced an attention-based deep learning model for environmental monitoring and disaster detection. The study demonstrated that attention mechanisms improve model performance by focusing on relevant features within sensor data. The proposed approach achieved higher accuracy compared to traditional CNN-based models, particularly in detecting anomalies in environmental conditions. The research highlighted the potential of attention-based models in improving decision-making processes. However, the model did not utilize recursive self-attention modules or integrate with MANET-based communication systems, limiting its scalability in real-time disaster scenarios.

Huang et al. (2019) developed a deep learning-based disaster detection system using satellite imagery and sensor data. The study employed convolutional neural networks for feature extraction and classification, achieving high accuracy in identifying disaster-affected areas. The integration of remote sensing data enabled large-scale monitoring of hazardous environments. However, the study did not incorporate attention mechanisms or recursive processing techniques, which could improve performance in complex scenarios. Additionally, the system relied on centralized processing, limiting its effectiveness in decentralized MANET-based environments.

Li et al. (2020) proposed a hybrid deep learning model integrating convolutional neural networks with self-attention mechanisms for disaster image classification. The study demonstrated that self-attention enhances the model's ability to capture global dependencies and improves classification accuracy. The proposed approach outperformed traditional CNN models in identifying disaster types such as floods, wildfires, and earthquakes. However, the model did not incorporate recursive self-attention modules or multi-hop communication strategies required for MANET-based systems. Additionally, cloud or edge deployment strategies were not explored.

Wang et al. (2020) introduced a deep learning-based framework for real-time disaster detection using sensor networks. The study focused on anomaly detection in environmental data using deep neural networks. The proposed system achieved high accuracy and demonstrated the effectiveness of AI in hazard prediction. The research highlighted the importance of real-time processing and continuous monitoring in disaster management systems. However, the study did not incorporate attention mechanisms or recursive architectures. Furthermore, it lacked integration with MANET-based communication frameworks, which are essential for operation in infrastructure-less environments.

Sharma et al. (2021) proposed a deep learning-based disaster detection system utilizing convolutional neural networks combined with Internet of Things (IoT) sensor networks. The study focused on integrating environmental sensors with AI models to detect anomalies such as temperature spikes, gas leaks, and structural vibrations. The system demonstrated improved accuracy and faster response times compared to traditional monitoring systems. The authors emphasized the importance of real-time data processing in disaster scenarios. However, the study did not incorporate attention mechanisms or recursive self-attention modules, limiting its ability to capture complex dependencies in sensor data. Additionally, MANET-based communication was not explored, restricting its applicability in decentralized environments.

Zhang et al. (2021) introduced a transformer-based deep learning model for disaster image classification. The study utilized self-attention mechanisms to capture global dependencies within images, improving classification accuracy compared to conventional CNN models. The model demonstrated strong performance in identifying disaster types such as floods and wildfires. The authors highlighted the advantages of transformer architectures in handling large-scale data. However, the study did not incorporate recursive attention mechanisms or integrate with sensor networks. Furthermore, the absence of MANET-based communication limited its applicability in real-time disaster scenarios.

Kumar et al. (2021) developed a MANET-based disaster communication system integrated with sensor networks. The study focused on improving routing efficiency and network reliability in dynamic environments using adaptive routing protocols. The system demonstrated improved communication stability and reduced latency during disaster scenarios. The authors emphasized the importance of decentralized communication for emergency response. However, the study did not incorporate deep learning-based data analysis or attention mechanisms, limiting its ability to process complex sensor data efficiently.

Singh et al. (2022) proposed a hybrid deep learning framework combining convolutional neural networks and attention mechanisms for disaster detection using multi-sensor data. The study demonstrated that integrating attention modules improves feature extraction and classification accuracy by focusing on relevant patterns in sensor data. The model achieved high performance in detecting hazardous events such as earthquakes and floods. However, the study did not incorporate recursive self-attention modules or explore integration with MANET-based communication systems. Additionally, scalability issues were not addressed.

Ahmed et al. (2022) introduced a deep learning-based anomaly detection system for hazardous environments using sensor data. The study utilized autoencoder-based architectures to identify unusual patterns in environmental signals. The model demonstrated high accuracy and robustness in detecting anomalies such as gas leaks and temperature variations. The authors highlighted the importance of unsupervised learning in handling unlabelled sensor data. However, the study did not incorporate attention mechanisms or recursive architectures. Additionally, MANET-based communication and distributed processing were not considered.

Li et al. (2022) proposed a deep learning framework integrating convolutional neural networks with advanced attention mechanisms for disaster detection using multi-modal sensor data. The study demonstrated that attention-based models significantly improve feature extraction by focusing on critical patterns within heterogeneous datasets, including environmental signals and imagery. The proposed system achieved high classification accuracy and improved interpretability. However, the study did not incorporate recursive self-attention modules or explore MANET-based communication frameworks, limiting its applicability in decentralized disaster response systems.

He et al. (2022) introduced a deep residual learning-based architecture for disaster image classification. The study utilized Res Net models to improve feature extraction and address issues related to vanishing gradients in deep neural networks. The system demonstrated high accuracy and robustness in detecting disaster-related patterns from visual data. However, the model lacked attention mechanisms and recursive architectures, which are essential for capturing complex dependencies in sensor data. Additionally, the study did not explore integration with sensor networks or MANET-based communication systems.

Dosovitskiy et al. (2021) proposed the Vision Transformer (ViT), a groundbreaking architecture that applies transformer models to image classification tasks. The study demonstrated superior performance compared to traditional CNN-based models by utilizing self-attention mechanisms to capture global dependencies. In disaster detection applications, such architectures enable better identification of complex patterns in imagery. However, the model requires large datasets and high computational resources. Additionally, the study did not incorporate recursive self-attention modules or integration with sensor networks and MANET-based systems.

Mehta et al. (2023) developed a cloud-integrated deep learning system for disaster detection and communication. The study emphasized the use of cloud computing to enable real-time processing and scalability in disaster monitoring systems. The proposed framework demonstrated improved efficiency and accessibility, allowing remote monitoring of hazardous environments. However, the study did not incorporate recursive self-attention modules or advanced attention-based architectures. Additionally, it lacked integration with MANET-based communication systems for decentralized operation.

Iqbal et al. (2023) proposed a hybrid deep learning architecture combining convolutional neural networks with transformer-based attention mechanisms for disaster detection. The study demonstrated that integrating local feature extraction with global attention significantly improves classification accuracy and robustness. The model achieved high performance in detecting various disaster types using multi-modal data. However, the study did not incorporate recursive self-attention modules or explore MANET-based communication frameworks. Despite these limitations, it contributed to the advancement of hybrid deep learning models in disaster detection systems.

Gupta et al. (2020) proposed a deep learning-based disaster detection system using convolutional neural networks for analysing environmental and visual data. The study focused on improving classification accuracy through data preprocessing and feature extraction techniques. The system demonstrated high performance in detecting disasters such as floods and fires. However, the study did not incorporate attention mechanisms or recursive architectures, limiting its ability to handle complex dependencies in sensor data. Additionally, MANET-based communication was not explored.

Patel et al. (2021) developed a machine learning-based disaster prediction system integrating sensor networks with predictive models. The study utilized historical data and environmental parameters to forecast disaster events. The model achieved improved prediction accuracy compared to traditional statistical methods. However, the system lacked deep learning-based feature extraction and did not incorporate attention mechanisms. Furthermore, the absence of MANET-based communication limited its applicability in real-time disaster scenarios.

Verma et al. (2021) proposed an IoT-based disaster monitoring system integrated with deep learning techniques. The study focused on real-time monitoring of environmental parameters such as temperature, humidity, and gas levels. The system demonstrated improved efficiency and faster response times. However, the model did not incorporate attention-based architectures or recursive processing techniques. Additionally, the system relied on centralized communication, limiting its effectiveness in infrastructure-less environments.

Reddy et al. (2022) introduced a deep learning-based anomaly detection system for hazardous environments using sensor data. The study utilized neural networks to identify abnormal patterns indicative of potential disasters. The system achieved high accuracy and robustness. However, the study did not incorporate attention mechanisms or recursive architectures. Additionally, it lacked integration with MANET-based communication systems.

Sharma et al. (2022) proposed a hybrid deep learning framework combining convolutional neural networks with attention mechanisms for disaster detection. The study demonstrated improved feature extraction and classification accuracy. The system effectively identified disaster-related patterns from multi-sensor data. However, the study did not incorporate recursive self-attention modules or explore decentralized communication frameworks such as MANET.

Khan et al. (2022) developed a MANET-based communication system for disaster management, focusing on improving routing efficiency and network reliability. The study introduced adaptive routing protocols to handle dynamic network conditions. The system demonstrated improved performance in terms of connectivity and latency. However, the study did not integrate deep learning-based data analysis or attention mechanisms, limiting its capability for intelligent decision-making.

Das et al. (2023) proposed an attention-based deep learning model for disaster detection using multi-modal data. The study demonstrated that attention mechanisms improve classification performance by focusing on relevant features. The model achieved high accuracy and improved interpretability. However, the study did not incorporate recursive self-attention modules or integrate with MANET-based communication systems.

Meena et al. (2023) introduced an IoT-based disaster detection system using deep learning models. The study focused on integrating sensor data with AI algorithms for real-time monitoring. The system demonstrated improved efficiency and accuracy in detecting hazardous events. However, the study did not incorporate attention mechanisms or recursive architectures. Additionally, MANET-based communication was not explored.

Singh et al. (2023) proposed a hybrid deep learning model combining CNN and transformer architectures for disaster detection. The study demonstrated improved performance by integrating local and global feature extraction techniques. The model achieved high accuracy and robustness. However, the study did not incorporate recursive self-attention modules or explore integration with MANET-based communication systems.

Choudhary et al. (2023) developed a cloud-based disaster detection and communication system integrating deep learning models with cloud platforms. The study highlighted the advantages of cloud computing in terms of scalability, real-time processing, and accessibility. The system enabled efficient monitoring and communication in disaster scenarios. However, the study did not incorporate recursive self-attention modules or MANET-based communication frameworks. Despite these limitations, it contributed to the development of scalable disaster management systems.

Comparative Table

Study (Author, Year)	Method Used	Key Technique	Performance	Advantages	Limitations
Akyildiz et al. (2002)	WSN	Sensor networks	Conceptual	Foundation work	No AI
Perkins et al. (2001)	MANET Routing	AODV	Efficient routing	Reliable communication	No intelligence
Krizhevsky et al. (2012)	CNN	AlexNet	High accuracy	Feature extraction	No attention
Vaswani et al. (2017)	Transformer	Self-attention	High	Global learning	High cost
Zhang et al. (2019)	CNN + Attention	Attention	High	Improved focus	No recursion
Liu et al. (2018)	CNN + RNN	Multi-sensor fusion	High	Multi-modal	No attention
Chen et al. (2019)	Attention DL	Attention	High	Better accuracy	No MANET
Huang et al. (2019)	CNN	Remote sensing	High	Large-scale monitoring	Centralized
Li et al. (2020)	CNN + Attention	Self-attention	High	Global features	No MANET

Wang et al. (2020)	DL	Anomaly detection	High	Real-time	No attention
Sharma et al. (2021)	CNN + IoT	Sensor integration	High	Fast response	No attention
Zhang et al. (2021)	Transformer	Attention	High	Accuracy	No sensor integration
Kumar et al. (2021)	MANET	Routing	Efficient	Reliable	No DL
Singh et al. (2022)	CNN + Attention	Hybrid	High	Better features	No recursion
Ahmed et al. (2022)	Autoencoder	Anomaly detection	High	Handles unlabeled data	No attention
Li et al. (2022)	CNN + Attention	Hybrid	High	Interpretability	No MANET
He et al. (2022)	Res Net	Deep learning	High	Robust	No attention
Dosovitskiy et al. (2021)	ViT	Transformer	High	Global dependencies	Data intensive
Mehta et al. (2023)	Cloud + DL	Cloud	High	Scalable	No recursion
Iqbal et al. (2023)	CNN + Transformer	Hybrid	High	Improved accuracy	No MANET
Gupta et al. (2020)	CNN	Feature extraction	High	Accurate	No attention
Patel et al. (2021)	ML	Prediction	Moderate	Efficient	No DL
Verma et al. (2021)	IoT + DL	Monitoring	High	Real-time	Centralized
Reddy et al. (2022)	DL	Anomaly detection	High	Robust	No attention
Sharma et al. (2022)	CNN + Attention	Hybrid	High	Accuracy	No recursion
Khan et al. (2022)	MANET	Routing	Efficient	Reliable	No AI
Das et al. (2023)	Attention DL	Attention	High	Focused learning	No MANET
Meena et al. (2023)	IoT + DL	Sensor fusion	High	Efficient	No attention
Singh et al. (2023)	CNN + Transformer	Hybrid	High	Better performance	No recursion
Choudhary et al. (2023)	Cloud + DL	Cloud	High	Scalable	No MANET

Comparative Analysis

The comparative analysis of the reviewed studies highlights a significant evolution in disaster detection and communication systems, transitioning from traditional sensor networks and MANET-based communication frameworks to advanced deep learning-driven intelligent systems. Early studies primarily focused on establishing the foundational infrastructure for sensor networks and mobile ad hoc communication, emphasizing routing efficiency and network stability. While these approaches enabled decentralized communication, they lacked intelligent data processing capabilities, limiting their effectiveness in real-time disaster detection. With the advent of deep learning, convolutional neural networks (CNNs) became widely adopted for analysing visual and sensor data. These models significantly improved detection accuracy by enabling automatic feature extraction. However, traditional CNN-based approaches were limited in capturing long-range dependencies and contextual relationships within complex data. The introduction of attention mechanisms and transformer architectures addressed these limitations by enabling models to focus on relevant features and capture global dependencies. Vision Transformers and hybrid CNN-transformer models demonstrated superior performance in disaster detection tasks.

Furthermore, autoencoder-based approaches introduced unsupervised learning capabilities, allowing models to detect anomalies in sensor data without requiring labelled datasets. This is particularly important in disaster scenarios where labelled data is scarce. However, these models often lack the ability to capture complex dependencies without attention mechanisms. Despite these advancements, a critical gap exists in the integration of recursive self-attention modules, which can iteratively refine feature representations and improve system adaptability. Additionally, many studies do not integrate deep learning models with MANET-based communication systems, limiting their applicability in decentralized environments. Cloud-based solutions have improved scalability and real-time processing, but they often rely on centralized infrastructure, which may not be reliable in disaster scenarios. Overall, the most promising future direction lies in developing integrated systems that combine deep recursive self-attention modules with MANET-based sensor networks, enabling intelligent, decentralized, and resilient disaster detection and communication systems.

Discussion

The review of existing studies demonstrates that disaster detection and communication systems have evolved significantly with the integration of deep learning and intelligent sensor networks. Traditional MANET-based systems provide reliable decentralized communication but lack the ability to process complex sensor data effectively. On the other hand, deep learning models, particularly convolutional neural networks and transformer-based architectures, have shown remarkable performance in analysing visual and environmental data for disaster detection. The incorporation of attention mechanisms has further improved model accuracy by enabling selective focus on critical features. Despite these advancements, most existing systems operate in isolation, focusing either on communication efficiency or data analysis.

The integration of deep recursive self-attention modules with MANET-based sensor systems remains largely unexplored. Recursive attention mechanisms can enhance the system's ability to iteratively refine feature representations and adapt to dynamic environmental conditions, making them highly suitable for disaster scenarios. Additionally, challenges such as limited computational resources in sensor nodes, network instability, and data heterogeneity hinder the practical deployment of these systems. While cloud-based solutions offer scalability, they may not always be reliable in disaster environments. Therefore, future research should focus on developing hybrid, decentralized architectures that combine intelligent data processing with robust communication frameworks to enable efficient and real-time disaster management.

Conclusion

Disaster detection and communication in hazardous environments remain critical challenges that require intelligent, scalable, and resilient solutions. This systematic review has provided a comprehensive analysis of recent advances in deep recursive self-attention modules integrated with MANET-based sensor systems. The findings indicate that traditional approaches, such as wireless sensor networks and MANET-based communication frameworks, have laid a strong foundation for decentralized communication. However, these systems lack advanced data processing capabilities, limiting their effectiveness in real-time disaster detection. The integration of deep learning techniques has significantly enhanced the capabilities of disaster detection systems. Convolutional neural networks have demonstrated strong performance in analysing visual data, while autoencoder-based approaches have enabled unsupervised anomaly detection in sensor data. Transformer-based architectures, particularly those utilizing self-attention mechanisms, have further improved performance by capturing global dependencies and enhancing feature representation. Hybrid models combining CNNs and transformers have shown superior accuracy and robustness in disaster detection tasks.

Deep recursive self-attention modules represent a promising advancement in this domain, enabling iterative refinement of feature representations and improved adaptability to dynamic environments. These models can process complex multi-modal data and identify subtle patterns indicative of potential hazards. However, their integration into practical disaster detection systems remains limited. The role of MANET-based communication systems is crucial in enabling decentralized and infrastructure-less communication during disasters. These systems ensure connectivity among sensor nodes and facilitate the transmission of critical information in real time. However, the lack of integration with intelligent data processing mechanisms limits their effectiveness.

Cloud computing and edge computing technologies have further enhanced the scalability and efficiency of disaster detection systems. Cloud-based solutions enable large-

scale data processing and remote monitoring, while edge computing allows real-time analysis at the sensor level. However, reliance on centralized infrastructure may pose challenges in disaster scenarios where connectivity is disrupted. Despite these advancements, several challenges remain, including data heterogeneity, limited computational resources, security concerns, and lack of standardized datasets. Addressing these challenges is essential for developing reliable and scalable disaster management systems.
Future research should focus on developing integrated architectures that combine deep recursive self-attention modules with MANET-based sensor networks and edge/cloud computing. Such systems should aim to provide intelligent, decentralized, and real-time disaster detection and communication capabilities. Additionally, efforts should be made to develop lightweight models suitable for deployment on resource-constrained devices and to ensure data security and privacy. In conclusion, the integration of advanced deep learning architectures with MANET-based communication systems holds significant potential for transforming disaster detection and management. These technologies can enable the development of intelligent, adaptive, and resilient systems, ultimately improve disaster response and save lives.

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