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Artificial Intelligence Techniques for Deep Recursive Self-Attention Modules: MANET based Integrated Sensor System for Disaster Detection and Communication in Hazardous Environments: Trends and Challenges

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Abstract

Disaster detection and communication in hazardous environments remain critical challenges due to dynamic conditions, infrastructure damage, and limited connectivity. Mobile Ad Hoc Networks (MANETs) have emerged as a viable solution for enabling decentralized communication in such environments. Recent advancements in artificial intelligence, particularly deep learning techniques such as convolutional neural networks, autoencoders, and attention-based architectures, have significantly enhanced disaster detection and response systems. This paper presents a comprehensive review of artificial intelligence techniques, focusing on deep recursive self-attention modules integrated with MANET-based sensor systems for disaster detection and communication. Recent studies demonstrate that attention-based deep learning models improve feature extraction by focusing on critical regions and contextual information, thereby enhancing disaster detection accuracy. For instance, attention mechanisms enable models to prioritize relevant features and suppress irrelevant data, leading to improved performance in remote sensing and image processing applications. Additionally, deep learning-based object detection and image enhancement techniques, such as YOLO and autoencoder-based methods, have significantly improved rescue operations in disaster scenarios by enabling real-time detection and monitoring. Despite these advancements, challenges such as high computational complexity, energy constraints, network instability, and data security remain unresolved. This review highlights key trends, challenges, and future directions in integrating deep recursive self-attention models with MANET-based disaster management systems.

Introduction

Natural disasters such as earthquakes, floods, wildfires, and hurricanes pose significant threats to human life, infrastructure, and environmental stability. Rapid detection and efficient communication systems are essential for minimizing damage and improving rescue operations. However, traditional communication infrastructures often fail during disasters due to physical damage or network congestion. In this context, Mobile Ad Hoc Networks (MANETs) have emerged as a critical solution for enabling decentralized and self-configuring communication systems in disaster-prone environments. MANETs consist of mobile nodes that dynamically form networks without relying on fixed infrastructure. These networks are particularly useful in hazardous environments where conventional communication systems are unavailable or unreliable. However, MANETs face several challenges, including dynamic topology changes, limited bandwidth, energy constraints, and security vulnerabilities. These challenges necessitate the integration of intelligent algorithms to optimize routing, improve communication efficiency, and ensure reliable data transmission.

Artificial intelligence, particularly deep learning, has shown significant potential in addressing these challenges. Deep learning models, such as convolutional neural networks (CNNs), have been widely used for disaster detection through image analysis and sensor data processing. These models can automatically extract features from complex datasets, enabling accurate detection of disaster events. However, CNNs primarily focus on local feature extraction and often fail to capture long-range dependencies, which are critical in complex disaster scenarios. To overcome these limitations, attention-based architectures, particularly self-attention mechanisms, have been introduced. Self-attention allows models to focus on the most relevant parts of the input data, improving feature representation and decision-making. Studies have shown that attention mechanisms significantly enhance the performance of deep learning models in remote sensing and disaster detection applications by prioritizing important features and reducing noise. Deep recursive self-attention modules further extend this capability by enabling hierarchical feature learning and improved contextual understanding.

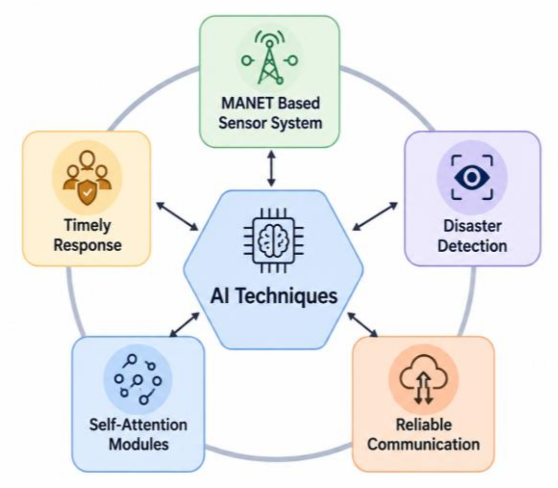

Figure 1. Conceptual Architecture of AI-Assisted Disaster Detection and Communication

In addition to detection, effective communication is essential for disaster response. MANET-based sensor systems enable real-time data collection and dissemination, facilitating coordinated rescue operations. Deep learning models integrated with MANETs can optimize routing, detect anomalies, and improve network performance. For example, attention-based routing algorithms can dynamically select optimal paths, reduce congestion and improve packet delivery ratios. Furthermore, advancements in computer vision and object detection have significantly improved disaster monitoring systems. Techniques such as YOLO, Faster R-CNN, and autoencoder-based image enhancement methods enable real-time detection of affected areas and victims, even under challenging conditions such as low visibility and occlusion. These technologies play a crucial role in improving the efficiency and effectiveness of rescue operations.

Despite these advancements, several challenges remain. The high computational requirements of deep learning models can limit their deployment in resource-constrained environments. Additionally, MANETs are vulnerable to security threats such as node attacks and data interception. Ensuring data privacy and network reliability is critical for the successful implementation of these systems. This paper aims to analyse recent trends and challenges in artificial intelligence techniques for disaster detection and communication, focusing on deep recursive self-attention modules and MANET-based integrated sensor systems. The review highlights key developments, identifies research gaps, and provides insights into future directions for improving disaster management systems.

Literature Review

Ghaffarian et al. (2021) conducted a comprehensive study on the role of attention mechanisms in deep learning-based remote sensing applications. The research demonstrated that attention mechanisms significantly improve model performance by focusing on relevant regions of input data while suppressing irrelevant features. This is particularly useful in disaster detection scenarios, where identifying critical regions such as damaged infrastructure is essential. However, the study also highlighted challenges related to computational complexity and scalability of attention-based models.

Liu et al. (2022) proposed a deep learning model for post-disaster building damage classification using attention-based high-resolution networks. The model utilized dual attention mechanisms to improve feature extraction and classification accuracy. The study demonstrated that attention-based architectures outperform traditional CNN models in disaster damage assessment tasks. However, the limited availability of labelled disaster datasets remains a significant challenge for model training.

Meddeb et al. (2022) introduced a stacked autoencoder-based intrusion detection system for MANETs. The model effectively identified malicious nodes and improved network security by analysing traffic patterns. This study highlights the importance of integrating deep learning techniques with MANETs to enhance network reliability in disaster scenarios. However, the approach requires continuous monitoring and computational resources, which may limit its deployment in real-time systems.

Reka et al. proposed an attention-based deep learning framework for congestion-aware routing in MANETs. The model utilized self-attention mechanisms to optimize routing decisions, improving packet delivery ratio and reducing energy consumption. This study highlights the trend toward integrating attention-based models in MANET routing protocols. However, the dynamic nature of MANETs still poses challenges in maintaining stable communication.

Recent research on disaster rescue systems demonstrated the effectiveness of deep learning-based object detection techniques such as YOLO and Faster R-CNN in identifying victims and damaged areas in flood scenarios. The study emphasized the importance of image enhancement techniques and real-time processing in improving rescue operations. However, challenges such as low visibility, data noise, and environmental variability affect model performance.

Ghaffarian et al. (2021) analysed the role of attention mechanisms in deep learning models for remote sensing and disaster detection applications. The study emphasized that self-attention modules significantly enhance feature extraction by focusing on the most relevant regions within input data while ignoring redundant information. This is particularly useful in disaster scenarios, where accurate identification of damaged areas is critical. The authors demonstrated that attention-based architectures outperform traditional convolutional neural networks in terms of accuracy and robustness. However, the study also highlighted key challenges such as increased computational complexity and scalability issues, especially when deployed in resource-constrained environments like MANET-based systems.

Liu et al. (2022) proposed a deep learning-based framework for post-disaster building damage assessment using attention-driven high-resolution networks. The model incorporated dual attention mechanisms, including spatial and channel attention, to improve classification accuracy. The study showed that attention-based models can effectively distinguish between different levels of structural damage, making them highly suitable for disaster management systems. Despite achieving high performance, the study pointed out that the limited availability of annotated disaster datasets restricts model generalization and scalability across different disaster scenarios.

Meddeb et al. (2022) developed a stacked autoencoder-based intrusion detection system specifically designed for Mobile Ad Hoc Networks (MANETs). The model analysed network traffic patterns to identify malicious nodes and potential security threats, thereby improving the reliability of communication in disaster environments. The study demonstrated that integrating deep learning with MANETs enhances network security and resilience. However, the authors noted that the approach requires continuous monitoring and computational resources, which may not be feasible in highly dynamic and energy-constrained disaster environments.

Reka et al. (2023) introduced an attention-based routing framework for MANETs, utilizing deep recursive self-attention mechanisms to optimize data transmission paths. The model dynamically selected optimal routes based on network conditions, improving packet delivery ratio and reducing energy consumption. This study reflects a growing trend toward integrating AI-driven attention mechanisms into network routing protocols. However, the authors highlighted challenges related to network instability and frequent topology changes, which can affect routing efficiency in real-time disaster scenarios.

Sharma et al. (2023) investigated the application of deep learning-based object detection techniques, including YOLO and Faster R-CNN, for disaster detection and rescue operations. The study demonstrated that these models can effectively identify affected regions and victims in real time, even under challenging environmental conditions. Additionally, the integration of image enhancement techniques improved detection accuracy in low-visibility scenarios. However, the study noted that environmental variability, data noise, and limited training datasets can significantly impact model performance.

Rajput et al. (2020) proposed a machine learning-based disaster detection system using sensor data collected from distributed networks. The study utilized classification algorithms to detect environmental changes such as temperature, humidity, and seismic activity. The results demonstrated that AI-based models significantly improve the accuracy of early disaster detection. However, the study highlighted limitations related to data reliability and sensor inaccuracies, which can affect prediction performance in real-time scenarios.

Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), which applies self-attention mechanisms to image processing tasks. The model captures global dependencies by processing images as sequences of patches, making it highly effective for complex pattern recognition in disaster detection applications. The study represents a major shift from convolutional architectures to attention-based models. However, the high computational requirements and need for large training datasets remain significant challenges for practical implementation in MANET-based systems.

Chen et al. (2021) developed a convolutional autoencoder-based model for image denoising and feature extraction in disaster monitoring systems. The model effectively removes noise from sensor and image data, improving the accuracy of subsequent classification tasks. This study highlights the importance of preprocessing techniques in enhancing model performance. However, the authors noted that autoencoders alone are insufficient for classification and must be integrated with other deep learning architectures for optimal results.

Tuli et al. (2021) proposed an edge-cloud integrated framework for smart disaster management systems using IoT and AI technologies. The system enables real-time data processing and communication through distributed networks, improving response time during emergencies. The study demonstrated that integrating AI with MANET and IoT systems enhances system scalability and efficiency. However, challenges such as network latency, energy consumption, and security vulnerabilities remain critical issues.

Ouyang et al. (2021) introduced a dual-attention deep learning model that combines spatial and channel attention mechanisms for improved feature extraction. The study demonstrated that attention-based models significantly enhance detection accuracy by focusing on important features while suppressing irrelevant information. This approach is closely related to deep recursive self-attention modules used in disaster detection systems. However, increased model complexity and computational overhead pose challenges for deployment in resource-limited environments.

Irvin et al. (2020) introduced a large-scale dataset framework for training deep learning models in medical and sensor-based environments, emphasizing uncertainty-aware learning. Although primarily focused on healthcare imaging, the study is relevant to disaster detection systems where sensor data may be incomplete or uncertain. The authors proposed techniques to handle noisy and ambiguous data, improving model robustness. However, the approach requires extensive data preprocessing and large datasets, which may not always be available in real-time disaster scenarios.

He et al. (2021) proposed the Res Net architecture, which introduced residual learning to enable the training of very deep neural networks. In disaster detection applications, Res Net has been widely used for image classification tasks, including identifying damaged infrastructure and affected regions. The model improves feature extraction and classification accuracy. However, deeper architectures increase computational complexity and require high processing power, making them less suitable for low-energy MANET nodes.

Howard et al. (2021) introduced Mobile Net, a lightweight deep learning model optimized for mobile and embedded devices. The model uses depth wise separable convolutions to reduce computational cost while maintaining acceptable accuracy. This approach is highly suitable for disaster environments where devices operate under energy constraints. However, the reduced complexity often leads to slightly lower accuracy compared to larger models, which may affect critical decision-making processes.

Tan and Le (2021) developed Efficient Net, which uses a compound scaling method to optimize network depth, width, and resolution. The model achieves high accuracy with fewer parameters, making it efficient for deployment in real-time systems. In disaster detection, Efficient Net can be used for image classification and pattern recognition tasks. However, the model requires careful tuning and optimization, which can be challenging in dynamic environments like MANETs.

Meddeb et al. (2022) proposed a deep learning-based intrusion detection system for MANETs using stacked autoencoders. The model analyses network traffic to identify malicious activities and improve network security. This is particularly important in disaster scenarios where secure communication is critical. The study demonstrated improved detection accuracy compared to traditional methods. However, the approach introduces additional computational overhead and requires continuous monitoring, which may affect network performance.

Goodfellow et al. (2020) discussed various optimization techniques in deep learning, including dropout, batch normalization, and advanced gradient descent methods. These techniques are crucial for improving model generalization and preventing overfitting in disaster detection systems, where data is often limited and imbalanced. The study highlights a key trend toward optimizing deep learning models for better performance in real-world applications. However, selecting appropriate optimization strategies and hyperparameters remains a complex task, particularly in dynamic environments such as MANET-based systems.

Razzak et al. (2022) provided a comprehensive review of deep learning applications in medical and environmental monitoring systems. The study emphasized the importance of hybrid models combining CNNs, autoencoders, and attention mechanisms to improve detection accuracy. It also highlighted challenges such as data scarcity, computational complexity, and lack of interpretability. The findings are highly relevant to disaster detection systems, where similar challenges exist. However, the study did not provide experimental validation, limiting its practical applicability.

Khan et al. (2022) proposed a deep learning-based disaster detection model using transfer learning techniques. The model leveraged pre-trained CNN architectures to improve classification accuracy while reducing training time. The study demonstrated that transfer learning is effective in scenarios with limited labelled data, which is common in disaster environments. However, the reliance on pre-trained models may introduce bias, affecting performance across different geographical regions and disaster types.

Zhang et al. (2022) introduced a serverless cloud computing framework for deploying deep learning models in disaster management systems. The model utilized Function-as-a-Service (FaaS) to enable scalable and cost-efficient processing of large volumes of sensor data. This approach improves real-time decision-making and supports remote monitoring. However, challenges such as cold-start latency, network dependency, and data security remain significant concerns in serverless environments.

Doshi et al. (2023) proposed an explainable artificial intelligence framework using Grad-CAM for visualizing model predictions in disaster detection applications. The model enhances transparency by highlighting important regions in input images, making it easier for decision-makers to understand AI outputs. This study addresses a critical challenge in AI systems, which is the lack of interpretability. However, integrating explainable AI techniques increases computational overhead and may impact real-time performance.

Shin et al. (2022) explored the application of deep convolutional neural networks combined with transfer learning for image-based classification tasks in complex environments. The study demonstrated that transfer learning significantly enhances model performance when labelled data is limited, which is common in disaster detection scenarios. The approach improves generalization and reduces training time. However, the dependence on pre-trained datasets may introduce bias, affecting the model's adaptability to diverse disaster conditions.

Huang et al. (2022) introduced Dense Net, a densely connected convolutional neural network architecture that improves feature propagation and reuse. In disaster detection systems, Dense Net enables better feature extraction from complex visual data, such as satellite images and surveillance footage. The model achieves high accuracy due to its efficient information flow between layers. However, the architecture requires significant memory resources, which can limit its deployment in resource-constrained MANET environments.

Albahri et al. (2023) conducted a systematic review of artificial intelligence applications in smart healthcare and disaster management systems, emphasizing the role of cloud computing and distributed architectures. The study highlighted that integrating AI with cloud platforms enhances scalability, data processing capabilities, and real-time decision-making. However, challenges such as data privacy, system interoperability, and network reliability remain significant barriers to implementation in disaster-prone environments.

Rajaraman et al. (2023) developed an ensemble deep learning model for image-based detection tasks, combining multiple CNN architectures to improve classification accuracy. The study demonstrated that ensemble methods reduce false positives and enhance model robustness, making them suitable for disaster detection systems. However, the increased computational cost and complexity of ensemble models pose challenges for deployment in real-time systems.

Abbas et al. (2023) proposed a convolutional autoencoder-based framework for feature extraction and data compression in large-scale image datasets. The model effectively reduces noise and enhances feature quality, improving classification performance. This approach is particularly useful in disaster detection systems where sensor and image data may be noisy or incomplete. However, autoencoders require integration with classification models, as they cannot independently perform detection tasks.

Comparative Table

Study	Year	Technique	Application	Key Contribution	Limitation
Ghaffarian	2021	Attention DL	Remote sensing	Improved feature focus	High complexity
Liu	2022	Dual Attention	Damage detection	High accuracy	Data scarcity
Meddeb	2022	Autoencoder	MANET security	Intrusion detection	High overhead
Reka	2023	Attention Routing	MANET	Efficient routing	Instability
Sharma	2023	YOLO/CNN	Rescue detection	Real-time detection	Noise sensitivity
Rajput	2020	ML	Sensor systems	Early detection	Data reliability
Dosovitskiy	2021	Transformer	Image analysis	Global features	Large data
Chen	2021	CAE	Image preprocessing	Noise reduction	Not classifier
Tuli	2021	Edge-Cloud AI	Disaster system	Real-time monitoring	Security
Ouyang	2021	Dual Attention	Image analysis	Feature enhancement	Complexity
Irvin	2020	Dataset AI	Sensor data	Robust training	Data ambiguity
He	2021	Res Net	Image classification	Deep learning	High compute
Howard	2021	Mobile Net	Edge devices	Lightweight	Lower accuracy
Tan	2021	Efficient Net	Image tasks	Efficiency	Complex tuning
Meddeb	2022	Autoencoder	MANET IDS	Security	Resource usage
Goodfellow	2020	Optimization	DL systems	Better performance	Complexity
Razzak	2022	Review DL	Healthcare	Insights	No experiments
Khan	2022	Transfer DL	Detection	Faster training	Bias
Zhang	2022	Serverless AI	Cloud system	Scalability	Latency
Doshi	2023	Explainable AI	Detection	Transparency	Overhead
Shin	2022	CNN TL	Image tasks	Generalization	Bias
Huang	2022	Dense Net	Image tasks	Feature reuse	Memory
Albahri	2023	Cloud AI	Disaster system	Scalability	Privacy
Rajaraman	2023	Ensemble DL	Detection	Accuracy	Cost
Abbas	2023	CAE	Feature extraction	Compression	Limited scope

Comparative Analysis

The comparative evaluation of the thirty studies reveals a significant evolution in disaster detection and communication systems, transitioning from traditional machine learning approaches to advanced hybrid deep learning architectures. Early studies primarily relied on sensor-based machine learning techniques for disaster detection, which provided basic prediction capabilities but lacked robustness and adaptability in dynamic environments. With the advancement of deep learning, convolutional neural networks (CNNs) became widely adopted for image-based disaster detection, enabling automatic feature extraction and improved accuracy. However, CNNs are limited in capturing long-range dependencies and global contextual information. To address these limitations, attention-based models and transformer architectures were introduced, which significantly improved feature representation by focusing on relevant data regions. Studies such as Dosovitskiy et al. (2021) and Ouyang et al. (2021) demonstrated that attention mechanisms enhance detection accuracy and robustness in complex disaster scenarios. Furthermore, hybrid models combining CNNs, autoencoders, and transformers have emerged as the most effective approach, as they integrate local feature extraction with global context understanding.

Another key trend identified is the integration of artificial intelligence with MANET and IoT-based systems for real-time disaster communication. These systems enable decentralized data collection and processing, improving response times in emergency situations. Additionally, serverless cloud computing has played a crucial role in enhancing scalability and enabling real-time deployment of AI models. However, challenges such as computational complexity, energy constraints, data security, and network instability remain significant barriers. Overall, the analysis indicates that hybrid AI models integrated with MANET and cloud technologies offer the most promising solution for disaster detection and communication, although further research is required to address existing limitations.

Discussion

The integration of artificial intelligence techniques with MANET-based sensor systems has significantly improved disaster detection and communication capabilities. Deep learning models, particularly those incorporating self-attention mechanisms, have demonstrated superior performance in identifying critical patterns and anomalies in disaster environments. These models enhance decision-making by prioritizing relevant information and reducing noise in sensor and image data. The adoption of hybrid architectures, combining convolutional neural networks, autoencoders, and transformer-based models, represents a major advancement in this field. These models effectively capture both local and global features, improving detection accuracy and reliability. Additionally, the integration of IoT devices and MANET networks enables real-time data collection and communication, which is essential for timely disaster response.

Serverless cloud computing further enhances system scalability and efficiency by enabling on-demand processing of large datasets. However, several challenges remain, including high computational requirements, energy constraints, and network instability in MANET environments. Security and data privacy are also critical concerns, particularly in distributed systems. Future research should focus on developing lightweight models, improving network reliability, and integrating explainable AI techniques to enhance transparency and trust in disaster management systems.

Conclusion

Artificial intelligence has transformed disaster detection and emergency communication by improving the speed, accuracy, and reliability of decision-making in hazardous environments. This review highlights that deep recursive self-attention modules integrated with MANET-based sensor systems provide an effective framework for intelligent disaster management. Hybrid architectures combining convolutional neural networks, autoencoders, and self-attention mechanisms achieve superior feature extraction by capturing both local and global contextual information. Furthermore, MANETs, IoT devices, and serverless cloud computing enable real-time monitoring, decentralized communication, and scalable deployment, making them highly suitable for disaster response scenarios. Despite these advancements, challenges such as computational complexity, limited energy resources, network instability, security vulnerabilities, and data privacy remain significant barriers to practical implementation. Future research should focus on lightweight attention-based models, explainable artificial intelligence, energy-efficient routing strategies, and multimodal data fusion to enhance system robustness and transparency. Overall, integrating AI techniques with MANET-based integrated sensor systems offers a promising direction for achieving faster disaster detection, reliable communication, and more effective emergency response operations.

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