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Review

Enhancing urban disaster response through AI-driven data visualization for real-time decision support

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Abstract: Urban areas face escalating threats from natural disasters due to climate change and rapid urbanization. This research explores how AI-driven data visualization enhances disaster response and supports real-time decision-making processes. The study proposes a reference architecture that integrates multiple data streams with adaptive visualization techniques, an advancement that improves situational awareness and coordination in emergency response environments. The research evaluates the Graph Attention Convolutional U-NET (GAC-UNET) model, which demonstrated high accuracy in flood detection tasks, achieving a 94% dice score and an 89% intersection over union (IoU). Case studies demonstrate practical benefits in real-world disaster situations, which include enhanced disaster impact prediction with greater precision, optimized resource allocation for maximum efficiency, and improved communication among diverse stakeholders in disaster response efforts. The findings reveal that AI-enabled data visualization significantly improves urban disaster response agility and accuracy, ultimately saving lives and reducing economic losses. The proposed framework adds operational capabilities to disaster management and offers improvements over traditional static dashboard systems. However, AI adoption in disaster management faces challenges such as data privacy concerns, security issues, ethical considerations in critical decision-making, and organizational resistance to new technology integration. This research emphasizes human-centered design principles and ethical AI governance frameworks for successful and responsible implementation. Future research should focus on generative AI models for scenario simulation, enhanced real-time predictive analytics capabilities, and community-driven platforms that improve collaboration and accelerate crisis decision-making processes.

Keywords: data visualization; disaster management; real-time decision support; emergency response; predictive analytics; situational awareness; artificial intelligence

1. Introduction and background

As climate patterns become increasingly unstable and urban populations continue to expand, disaster management systems face unprecedented pressure to evolve beyond conventional response methodologies. Recent catastrophic events underline this urgency, as Typhoon Mawar devastated infrastructure across the Philippines, Taiwan, and Japan, causing severe flooding and power outages that displaced thousands, left six people dead and five missing, injured ten others, and resulted in over $4.3 billion in damages [1]. Similarly, Hurricane Otis struck Acapulco, Mexico, as a Category 5 storm with winds reaching 270 km/h, killed at least 27 people, displaced over 34,000 families, left hundreds of thousands without electricity or communication, and caused more than $15 billion in damages while triggering widespread coastal erosion, landslides, and disease outbreaks [2].

The increasing frequency and intensity of natural disasters create substantial challenges for urban disaster management systems, necessitating innovative approaches to enhance preparedness and response capabilities [3,4]. Traditional disaster management approaches, often characterized by reactive protocols, struggle to address the evolving complexity of disaster threats [5]. Consequently, the integration of advanced technologies, particularly artificial intelligence (AI), has become essential for enhancing disaster management efficiency and effectiveness [3,6]. AI-enhanced data visualization plays a crucial role in this transformation by enabling the aggregation, analysis, and presentation of vast datasets from diverse sources to facilitate well-informed real-time decision-making for disaster management agencies. These technologies enhance situational awareness through data integration from weather monitoring systems, traffic databases, and social media platforms [7,8]. Real-time data collection through IoT devices enables cities to monitor environmental conditions such as air quality and water levels, which provides critical early warning capabilities and response coordination support [4,6].

Beyond enhancing situational awareness, AI algorithms facilitate optimal resource allocation by identifying at-risk areas through analysis of population density, geographical constraints, and historical disaster data. This targeted approach ensures efficient utilization of resources and emergency services, which ultimately reduces disaster impact [9,10]. Furthermore, predictive analytics, which utilizes machine learning and statistical models for data analysis [11], enables urban planners and disaster management agencies to simulate various disaster scenarios [4,7], which leads to improved preparedness strategies and enhanced strategic planning capabilities. The development of standardized frameworks that integrate multi-source data systems with advanced visualization tools represents a fundamental shift toward proactive disaster management. These frameworks establish the foundation for coordinated decision-making and interoperability between agencies and systems, ensuring that important information flows smoothly between everyone involved in disaster management responses [12], while supporting scalability across diverse urban environments, which includes smaller municipalities and resource-constrained regions that lack advanced infrastructure. The proposed framework demonstrates cross-regional adaptability through its modular design, which enables implementation in both resource-rich metropolitan areas and smaller cities with limited technological infrastructure, while maintaining core functionality through scalable component architecture.

The data collection layer aggregates real-time information from IoT sensors, social media feeds, and satellite imagery to provide comprehensive situational awareness for immediate threat assessment. The processing module transforms raw data into actionable intelligence through AI algorithms and predictive models, enabling automated threat detection and resource optimization. The visualization interface provides role-specific dashboards that support both tactical field operations and strategic command center decision-making, while communication protocols ensure seamless inter-agency coordination and real-time data synchronization during crisis situations.

Figure 1 demonstrates the comprehensive reference architecture showing how data sources, processing components, and visualization interfaces integrate within a unified disaster management structure. Each architectural component operates in coordination to ensure seamless information flow and rapid response capabilities during crisis situations, with a specific focus on inter-agency communication protocols. This architectural foundation establishes the technological framework necessary for implementing advanced AI methodologies that enhance emergency response capabilities and support complex decision-making processes during urban disasters.

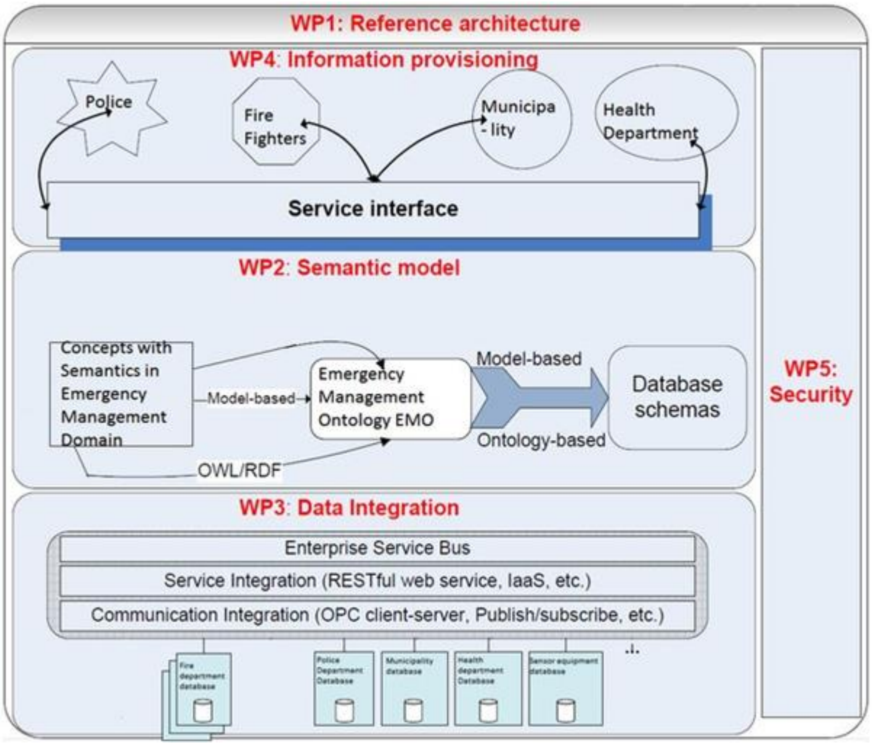

Figure 1. Reference architecture.

Source: Nguyen 2011.

2. AI technologies in data visualization for disaster management

The convergence of artificial intelligence and visualization technologies has fundamentally transformed how disaster management professionals interpret and utilize complex emergency information. AI technologies have become essential components for enhancing data visualization capabilities, particularly in supporting rapid decision-making processes during urban disaster scenarios. These technologies leverage advanced algorithms and machine learning methodologies to process and analyze extensive datasets, which enables responders to make informed decisions efficiently and effectively.

The Graph Attention Convolutional U-NET (GAC-UNET) model represents a significant advancement over traditional CNN and U-NET architectures in both performance and adaptability for emergency management applications [13]. Traditional CNN architectures process image data through standard convolutional layers without considering spatial relationships between different regions [14]. Standard U-NET models, while effective for basic segmentation tasks, lack the capability to focus attention on critical disaster-affected areas. The GAC-UNET model addresses these limitations through its Graph Attention mechanism, which enables the model to understand spatial relationships between different geographic regions and allocate computational resources to areas most relevant for disaster response. This attention mechanism allows the model to achieve superior performance in flood detection tasks, demonstrating enhanced adaptability to various urban environments and disaster scenarios compared to conventional approaches [13].

AI-driven pattern recognition tools excel at identifying trends and anomalies within large datasets, which highlights causal factors and temporal patterns that are crucial for disaster management services that require predictive capabilities based on historical data [15,16]. This functionality enables decision-makers to develop proactive disaster management strategies and resource allocation protocols. Natural language processing (NLP), a specialized field within artificial intelligence focused on computer-human language interaction, enables users to interact with data using natural language queries, making data insights accessible to non-technical personnel. This capability allows stakeholders to pose questions such as “What were the response times during the last major disaster?” and receive immediate, visual responses that facilitate rapid comprehension of complex situations [15,17]. As systems learn from user queries or questions, they improve their ability to provide relevant information and visualizations.

Real-time analysis capabilities are essential during emergency situations, and AI data visualization tools including Geographic Information Systems (GIS), Emergency Response Devices (ERDs), and advanced monitoring systems excel at processing live data streams to maintain current visualizations. Furthermore, automated analysis features enable these tools to automatically identify outliers, clusters, and correlations without requiring specific user requests [15,18]. This automation reduces response times and ensures that responders have access to the most current and relevant information for critical decision-making.

The implementation of predictive analytics within AI data visualization tools significantly enhances decision-making capabilities by forecasting potential outcomes and risk scenarios. This enables disaster management services to prepare for and respond effectively to evolving situations. For example, AI systems can suggest probable scenarios and optimal resource deployment strategies before disasters occur by analyzing historical response data [16,18]. AI visualization tools provide extensive customization capabilities, allowing users to select from various display formats and metrics that align with their specific objectives. This flexibility ensures that data visualizations are both accurate and tailored to the particular needs of disaster management teams, enhancing their ability to interpret complex data efficiently [17,19]. The integration of sophisticated models such as GAC-UNET, combined with natural language processing and real-time analytics, creates comprehensive decision-support systems that enhance situational awareness and response coordination capabilities, which establishes the foundation for practical applications in emergency management operations. Also, the technical capabilities outlined above demonstrate the transformative potential of AI technologies in disaster management visualization, setting the stage for examining specific real-world applications and implementation outcomes.

3. Applications in disaster management decision support systems

In scenarios where minutes can determine the difference between life and death, AI-driven visualization systems provide disaster management responders with exceptional situational awareness and robust decision-making support capabilities. AI-driven data visualization plays a crucial role in enhancing disaster management decision support systems within urban disaster contexts through advanced analytics and real-time data processing that increases awareness and accelerates decision-making efficiency for disaster management responders. AI technologies process and display extensive information from diverse sources such as incident reports, resource availability data, and historical records. This real-time analysis enables comprehensive understanding of ongoing emergencies and facilitates rapid, informed decision-making by responders [20,21]. One of the most valuable aspects of AI implementation in disaster management services is its predictive capability, which analyzes historical event data to forecast potential outcomes in current emergencies, supporting resource allocation and response prioritization strategies [21,22]. For example, during natural disaster events, AI systems can provide evacuation route simulations and optimal strategy recommendations by analyzing current traffic patterns and geographical constraints [23].

AI systems also streamline operations through automation of routine tasks, such as AI-driven chatbots that handle initial emergency call triage, reducing workload on human operators [22]. In addition, algorithms can analyze surveillance footage to identify hazards or locate individuals requiring assistance, enabling rapid and effective responder action [21,22]. Moreover, AI enhances communication within disaster management teams by automatically distributing alerts to appropriate personnel based on incident type and location, which ensures teams remain well-informed and coordinated during critical situations [20]. Likewise, centralized information hubs facilitate access to essential data, further improving collaboration among responders.

Generative AI provides substantial enhancements to disaster response efforts, particularly for natural disasters such as floods or forest fires, where generative models can simulate various environmental conditions to supplement existing datasets. This capability helps create detailed and clear imagery even when real-world data is unclear or incomplete due to adverse conditions [24]. Generative Adversarial Networks (GANs) are fundamental to this process, utilizing a generator to create data and a discriminator to verify authenticity, which results in increasingly realistic simulations [24]. Moreover, GAN-generated synthetic data enhances model robustness in data-sparse conditions through several key mechanisms. The generator component learns underlying patterns from available real disaster data and produces synthetic examples that fill critical data gaps, while the discriminator ensures these synthetic samples maintain statistical authenticity [25]. This process creates realistic training datasets that mirror actual disaster characteristics when original data is limited due to access restrictions or challenging environmental conditions [26]. The synthetic data augmentation enables emergency management systems to maintain predictive accuracy even when faced with incomplete information streams, particularly during active disasters or in remote areas where sensor deployment proves impractical, ultimately strengthening model performance and reliability in resource-constrained scenarios.

Recent studies demonstrate the effectiveness of AI-driven flood forecasting capabilities. For instance, research on flood risk prediction in Houston using Artificial Neural Networks (ANN) demonstrated the power of machine learning models for improving flood predictions, enhancing urban planning and preparedness for severe weather events [27]. NASA’s SPoRT program developed a machine learning tool for river flood prediction that provides advanced warnings more than two days ahead, proving invaluable for decision-making during flood events in Texas [28]. Ongoing advances in AI-driven data visualization have significantly improved urban flood management capabilities. For instance, the Graph Attention Convolutional U-NET (GAC-UNET) model effectively combines satellite imagery with AI analysis to accurately predict flood impacts, which achieved a 94% Dice score and 89% Intersection over Union (IoU) in identifying flooded areas [13]. The model treats flood detection as a binary segmentation problem, uses a U-Net structure enhanced with Graph Attention and Chebyshev convolution layers to better capture spatial relationships. The model was trained on a 290-image aerial flood dataset from Kaggle with ground truth labels manually annotated as binary masks with water areas marked as 1 and non-flooded areas as 0, representing 40.7% positive class pixels and 59.3% negative class pixels. Data preprocessing included 256 × 256 pixel resized images with augmentation through five crop segments per image and horizontal/vertical flips, with a 70/30 holdout split for training and validation. Transfer learning and model reprogramming techniques improved accuracy using limited datasets, with validation results that include a 94% Dice score (±2.1% confidence interval), 89% IoU (±1.8% confidence interval), and 91% mean Average Precision—mAP (±2.3% confidence interval). These performance metrics represent substantial improvements over traditional CNN approaches, which typically achieve 78%–82% accuracy in similar applications [13].

Furthermore, in response to increasing wildfire threats, California has integrated artificial intelligence into fire detection systems through the ALERTCalifornia program, which utilizes over 1150 AI-equipped cameras to monitor fire-prone areas for enhanced early detection and response capabilities. These cameras analyze live video feeds to detect early wildfire indicators such as smoke plumes, with the system successfully identifying more than 1200 fires, which demonstrates AI detection outperforming human 911 callers approximately one-third of the time [29]. For example, in December 2023, the AI system detected a nighttime fire in an Orange County canyon, which enabled a rapid response that prevented significant damage. This early detection capability proved crucial to reduce response times and to lessen the impact of wildfires [29]. During Hurricane Ian, researchers developed the CVDisaster system, which utilized AI to enhance disaster response through real-time location and damage assessment information by combining street-view images and high-resolution satellite data. The AI model achieved over 80% accuracy in locating affected areas and 75% accuracy in estimating damage severity, which provides essential information for disaster management responders to prioritize resource allocation and aid distribution effectively. The CVDisaster system demonstrates how

AI-driven data visualization can enhance awareness and decision-making during urban disasters [30].

Table 1 presents a comprehensive comparative analysis of key AI visualization technologies used in disaster management, compiled through systematic review of multiple secondary sources and research studies, to assess their technical capabilities, implementation requirements, and performance across different disaster scenarios.

Table 1. Comparative analysis of AI visualization technologies in disaster management.

Technology	Primary Application	Technical Approach	Performance Metrics	Implementation Complexity
Deep Learning for Image Analysis	Flood detection, fire spread mapping	CNN, U-NET architectures	85%–94% accuracy [31] (context-dependent)	High—requires specialized hardware
NLP for Social Media Analysis	Public sentiment analysis, need identification	BERT, transformers	78%–82% precision in identifying critical needs [32]	Medium—language dependencies
Predictive Analytics for Resource Allocation	Response optimization	Random forests, ensemble methods	15%–30% improvement in resource efficiency [33]	Medium—requires quality historical data
Real-time GIS Visualization	Situational awareness	Graph-based networks, spatial databases	Response time < 2 s for visualization updates [34]	Low-Medium—integrates with existing GIS

The practical applications in **Table 1** demonstrate measurable benefits of AI integration in disaster management in terms of response accuracy, resource allocation efficiency, and inter-agency coordination. These technological advances establish a strong foundation for enhanced disaster management capabilities while revealing implementation challenges that require careful consideration for successful organizational adoption.

4. Challenges and limitations of AI integration

Despite AI's significant transformative potential for operational enhancement, implementing AI-driven visualization tools into disaster management systems presents substantial technical, organizational, and ethical challenges that require resolution. Data security and privacy concerns represent one of the most critical issues, as AI tools collect and process extensive health and location data, potentially exposing organizations to cyber threats. The WannaCry ransomware attack in 2017, which affected patient data at hospitals worldwide [35], exemplifies this vulnerability. Consequently, ensuring data privacy while utilizing AI capabilities is crucial for maintaining public trust and complying with legal requirements.

Organizational resistance to change represents another major obstacle to AI technology adoption. Local government leaders often exhibit risk-averse tendencies regarding new technologies due to concerns about potential failures or negative consequences [36]. This apprehension can hinder innovation and prevent adoption of AI solutions that could enhance operational efficiency. However, effective AI implementation in disaster management requires comprehensive staff training and skill development to manage and interpret AI-generated information. Many organizations may lack the resources or infrastructure to provide adequate training, complicating successful AI tool integration [37]. Without proper staff preparation, the potential benefits of AI-driven data visualization may not be fully realized. Integrating AI solutions with existing organizational processes and legacy systems can be complex and resource intensive. Many organizations encounter compatibility issues and challenges ensuring smooth data flow across different platforms [37], which leads to fragmented workflows that reduce the overall effectiveness of AI applications in disaster management decision-making.

As AI systems become more prevalent, ethical decision-making becomes increasingly important. For example, recovery robots deployed after disasters must prioritize certain areas, raising ethical questions about fairness in resource allocation [38]. The ethical implications of AI's role in decision-making, particularly in critical situations such as disaster response, require careful consideration and management to avoid exacerbating existing inequalities. AI models depend heavily on access to high-quality, consistent data. The COVID-19 pandemic highlighted significant challenges in integrating data from different sources, which can limit AI application effectiveness in real-time situations [39]. Inconsistent data can result in inaccurate information and reduced trust in AI-driven decision support systems. While AI can process extensive datasets, it lacks the emotional intelligence and cultural awareness that human responders bring to disaster situations. Therefore, establishing an appropriate balance between AI's analytical capabilities and human judgment is essential for effective human-machine collaboration [39]. Leaders need to implement strategies that encourage collaboration between AI systems and human responders to ensure ethical and effective decision-making during emergencies.

A significant technical challenge identified in recent studies is "visualization overload", which occurs when disaster management professionals become overwhelmed by the volume and complexity of data visualizations [40]. Research indicates that increasing data variables or complexity raises the mental effort required to understand visualizations, potentially hindering information extraction during high-stress situations. This emphasizes the importance of human-centered design approaches that balance comprehensive data provision with user cognitive load considerations [40]. To address visualization overload, several mitigation strategies exist. These mitigation approaches include user profiling systems that assess individual cognitive capacity and experience level to customize information presentation [41], role-specific dashboards that filter and prioritize data based on job function to ensure decision-makers receive only relevant content, adaptive interface design that adjusts complexity based on stress indicators and decision urgency, and progressive disclosure methods that present information in manageable layers users access as needed [42]. Such strategies collectively reduce cognitive burden while maintaining access to critical information during emergency situations. The implementation challenges highlight the necessity for comprehensive adoption strategies that address technical compatibility, organizational culture, and human factors to ensure successful AI integration in disaster management systems. The identification of these barriers provides the foundation for developing effective solutions and establishing best practices for responsible AI deployment in emergency response incidents. Understanding these implementation challenges provides essential context for exploring future research directions that address current limitations while expanding AI capabilities in disaster management applications.

5. Future directions and opportunities

The future of AI-driven disaster management systems presents promising opportunities for innovations that could fundamentally transform how cities prepare for, respond to, and recover from emergencies. Building upon the established GAC-UNET performance benchmarks and identified visualization overload challenges, future developments should focus on adaptive human-machine collaboration systems that respond dynamically to user cognitive load and situational complexity.

The next evolutionary step in AI-driven data visualization for disaster management should emphasize improving human-machine collaboration, particularly in high-stress, critical situations. A promising approach involves developing visualization systems that adapt to user mental workload and role requirements, which adjust data quantity, format, and presentation in real-time to help disaster management responders avoid information overload and focus on critical details. This could be achieved through monitoring user behavioral and physiological indicators, such as screen interaction patterns or decision complexity metrics, to automatically simplify data views as needed.

Another opportunity involves creating integrated urban emergency coordination centers that serve as centralized, real-time hubs for emergency data analysis. These centers would combine data from public infrastructure, social media platforms, citizen reports, and disaster management services into unified visual dashboards powered by AI technologies. Unlike traditional command centers, these environments would emphasize continuous learning capabilities, where AI systems simulate developing disaster scenarios and provide predictive recommendations for resource allocation and inter-agency coordination.

Generative AI models, particularly Generative Adversarial Networks (GANs), offer substantial potential for scenario simulation and real-time data enhancement. GAN-generated synthetic data enhances model robustness in data-sparse conditions through several key mechanisms. When real-world disaster data is limited or incomplete due to access restrictions or challenging environmental conditions, GANs create realistic synthetic datasets that mirror the statistical properties of actual disaster scenarios. The generator component learns underlying patterns from available real data and produces synthetic examples that fill data gaps, while the discriminator ensures these synthetic samples maintain authenticity. This process strengthens model performance in situations where traditional data collection methods prove insufficient, such as during active disasters or in remote areas where sensor deployment is impractical. Synthetic data augmentation enables emergency management systems to maintain accuracy even when faced with incomplete information streams, which create detailed visualizations even when data is limited or unclear due to difficult conditions.

There is substantial untapped potential in using visualization platforms that involve local communities in preparing for disasters. Given this, community-based simulation tools that use extended reality (XR), virtual reality (VR) and augmented reality (AR) technologies offer significant opportunities for enhanced disaster preparedness. These tools would function as accessible, user-centered platforms that allow community members to experience simulated disaster scenarios through virtual and augmented reality interfaces. Implementation would involve developing lightweight XR applications that operate on standard mobile devices and tablets to ensure widespread accessibility without requiring specialized hardware. These simulation environments would integrate with existing public platforms such as municipal websites, emergency alert systems, and social media channels to reach diverse community populations. Citizens could access interactive disaster simulations that demonstrate evacuation routes, emergency procedures, and resource locations specific to their neighborhoods. Public integration would occur through QR codes placed in community centers, schools, and public buildings that link to simulation experiences, while mobile applications would connect with established emergency notification systems to provide personalized disaster scenarios based on user location and local risk factors. These community-centered tools would collect anonymized user interaction data to improve AI models while providing residents with practical experience in emergency response procedures.

Future tools should incorporate simulation-based environments, potentially using augmented or virtual reality technologies that allow residents, planners, and responders to interact with predictive disaster models. These participatory tools would enhance local awareness and preparedness while improving AI model quality through incorporation of community insights and real-world experiences. As urban populations become increasingly diverse, AI-driven visual tool design must prioritize fairness and accessibility. Interfaces should support multiple languages, accommodate users with varying technical skill levels, and adapt to the communication needs of different community groups. This inclusive approach ensures that essential information reaches all community members during emergencies.

There is also potential for developing community-centered resilience networks that shift focus from top-down disaster management to collaborative networks that empower communities to actively participate in disaster response. Moreover, utilizing AI-driven systems to simulate infrastructure performance under disaster conditions will help cities prepare for future climate-related impacts. To support these advancements, cities need to invest in comprehensive workforce development programs that train responders not only in technology utilization but also in AI literacy, bias recognition in AI systems, and ethical reasoning applications. These skills will be crucial as AI systems become more integrated into real-time decision-making during crisis situations. Creating ethical AI governance frameworks will ensure that AI deployments adhere to transparency and accountability standards while supporting interdisciplinary knowledge integration, breaking down silos between sectors such as public health, infrastructure, and climate science to improve decision-making in complex disaster situations.

Future research must address integration challenges between XR-based community tools and institutional emergency management systems to ensure seamless information flow during actual disasters. The combination of generative AI models, community-based simulation platforms, and ethical governance frameworks will create more resilient and inclusive emergency management systems that serve diverse urban populations effectively, ultimately advancing both technological capabilities and community preparedness for future disaster scenarios. The future directions build upon current technological capabilities while addressing identified limitations, establishing a pathway toward more adaptive, inclusive, and effective disaster management systems.

6. Conclusion

AI-driven data visualization has emerged as a transformative tool for enhancing urban disaster management through enabling real-time data analysis and predictive capabilities that shift disaster management from reactive to proactive approaches, improving resource allocation and enhancing urban disaster preparedness. This research provides three concrete contributions to the field. First, it presents a comprehensive comparative analysis framework for evaluating AI visualization technologies in disaster management contexts, as demonstrated in **Table 1**, establishing standardized evaluation criteria for future research. Second, it establishes performance benchmarks for the GAC-UNET model, which achieved a 94% dice score and 89% IoU in flood detection tasks, offering measurable standards for future flood prediction systems. Third, it proposes an ethical AI governance framework that addresses critical implementation challenges such as data privacy, organizational resistance, and human-centered design principles for responsible AI deployment in emergency contexts. The case studies and system architectures presented demonstrate how integrating multi-source data with adaptive visualization techniques can significantly enhance disaster management response coordination and effectiveness. However, challenges including data privacy protection, organizational change resistance, and training requirements must be addressed for successful implementation. Future directions include developing hybrid visualization environments that combine extended reality technologies with AI capabilities, implementing enhanced human-centered design approaches that address cognitive load management, and creating community-based simulation platforms that improve public preparedness and engagement. Effective disaster management will require collaboration between technology developers, government agencies, and communities to build resilient urban environments capable of effective crisis response.

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