Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 1, 1177-1188
2026
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v10i1.11904

Every second counts for search and rescue: A systematic review of TinyML drone

Liu Junchang[1], JosephNg Poh Soon[1*], Phan Koo Yuen[2], Wong See Wan[3]
[1]Institute of Computer Science and Digital Innovation, UCSI University, Kuala Lumpur, Malaysia; 1002475702@ucsiuniversity.edu.my (L.J.) joseph.ng@ucsiuniversity.edu.my (J.P.S.).
[2]Faculty of Information and Communication Technology, Universiti Tunku Abdul Rahman, Perak, Malaysia; phanky@utar.edu.my (P.K.Y.).
[3]Vise Trading, Penang, Malaysia; karenwsw@gmail.com (W.S.W.).

Abstract: This study explores the transformative potential of TinyML in unmanned aerial vehicles (UAVs) to address key inefficiencies in traditional search and rescue (SAR) operations, especially in the context of increasingly severe climate-related disasters. By analyzing peer-reviewed studies in major technical databases via the PRISMA guidelines, this work highlights advancements in edge computing, swarm intelligence, and multisensory integration, with a focus on fundamental contributions in embedded AI and autonomous navigation. UAVs supported by TinyML can achieve low-latency and energy-efficient real-time processing, thereby enhancing the efficiency of disaster relief operations in harsh environments. This study emphasizes the need to create synthetic datasets for underrepresented scenarios, conduct robustness tests under extreme conditions, and adopt privacy-focused decentralized learning. It connects technological progress with ethical issues such as monitoring risks and equitable access to disaster technologies. Future research directions can overcome current limitations, including insufficient validation in practical applications, fragmented policies, and high costs in resource-poor regions, through interdisciplinary collaboration, transforming theoretical advancements into scalable and socially responsible TinyML-UAV system solutions.

Keywords: *Artificial Intelligence, Disaster Rescue, Edge Artificial Intelligence, Image Processing, Sustainable Infrastructure, TinyML, UAV.*

1. Introduction

Currently, climate-driven disasters such as wildfires and floods occur frequently worldwide, highlighting the significant limitations of traditional search and rescue (SAR) operations in resource-poor areas with vulnerable populations [1]. Traditional methods rely on manual operation and simulation tools, often leading to delayed responses and increased risks for rescue workers [2]. The combination of unmanned aerial vehicles (UAVs) and TinyML has transformative potential, offering real-time, energy-efficient edge computing for disaster management [3]. Innovations like lightweight neural networks and sensor fusion significantly improve the detection of survivors in low-visibility environments [4], whereas federated learning frameworks enhance the adaptability of distributed UAV networks [5], these developments highlight the potential of TinyML-UAV systems in addressing increasing climate-related emergencies [6] such as scenarios requiring rapid assessment of infrastructure damage [6] or mixed vertical take-off and landing (VTOL) operations [7].

Although drone technology development in search and rescue operations has been rapid, several challenges remain. The literature on drone research often overlooks natural disasters in remote areas [8], lacks relevant training data, and does not focus sufficiently on government drone regulatory policies [9]. In addition, there are trust issues such as the lack of transparency in AI-driven systems

History: Received: 5 November 2025; Revised: 5 January 2026; Accepted: 12 January 2026; Published: 27 January 2026
* Correspondence: joseph.ng@ucsiuniversity.edu.my

[10]. These challenges highlight the urgent need for inclusive drone search and rescue technology solutions that balance innovation with social and economic equity in modern society [11, 12].

This paper summarizes the progress of tiny ML-UAV systems, tracing their evolution from the limitations of past disaster rescue technologies to future innovations. By analyzing peer-reviewed research, we evaluate innovative approaches such as cluster coordination for scalable disaster coverage, emphasizing ongoing advancements in the field [13] and biodegradable UAV design to reduce environmental impact [14]. For example, the use of generative AI to generate synthetic data can simulate underrepresented scenarios to mitigate geographical bias [15], whereas federated learning frameworks ensure privacy-sensitive model training. Transparent AI modules, such as explainable decision systems, address accountability issues, facilitate global regulatory coordination, and simplify cross-border tasks [16]. These methods aim to transform TinyML-UAV systems into resilient, fair tools capable of protecting vulnerable groups in various disaster environments. They can also be extended to applications like forest ecological monitoring [17] and underground infrastructure maintenance.

2. Evolution of Disaster Rescue Technologies from Past Limitations to Future Innovations

Historically, disaster rescue operations have faced significant challenges due to reliance on manual labor, fragmented communication systems, and delayed response times. Early approaches, such as 19th-century fire brigades and 20th-century motorized units, primarily used handheld tools and analogue technologies, often resulting in prolonged victim recovery efforts and high responder fatality rates [18]. For example, during the 1985 Mexico City earthquake, rescue teams manually sifted through debris for days, leading to preventable casualties caused by insufficient situational awareness [19]. Similarly, the 2004 Indian Ocean tsunami revealed critical deficiencies in real-time data collection, as responders relied on disjointed ground reports and static maps, significantly delaying life-saving interventions [20]. These limitations highlight the urgent need for technologies capable of functioning effectively in dynamic, high-risk environments while reducing human exposure [21].

The emergence of unmanned aerial vehicles (UAVs) in the 2010s marked a significant advancement. Initial deployments, such as during the 2010 Haiti earthquake, demonstrated UAVs' potential for aerial damage assessment, though they faced high costs and computational limitations. The late 2010s saw the integration of tiny machine learning (TinyML), which addressed these issues by enabling edge-based intelligence for real-time processing [22]. Advances in hardware, including ARM Cortex-M processors and TensorFlow Lite for microcontrollers, have progressed [23] and facilitated the execution of lightweight object detection models with minimal power consumption [7]. Advances in sensor fusion have further improved capabilities; hybrid systems combining LiDAR, thermal imaging, and acoustic sensors enhanced detection accuracy in obscured environments, as demonstrated during the 2023 Türkiye–Syria earthquakes.

Currently, the application of drones in disaster relief aligns more with Figure 1. Modern and future drone innovations emphasize scalability and adaptability. The federated learning framework enables distributed drone networks to collaboratively train models and optimize task allocation in multi-agent systems, thereby achieving large-scale coverage. Solar-powered designs and modular drones extend operational time while reducing costs, which is crucial for resource-scarce regions [24]. However, challenges remain: geographical bias in training data limits the model's generalizability in rural disasters such as landslides [6], and the fragmented regulation of beyond-visual-line-of-sight drone flight policies hinders cross-border deployment. Future development will focus on generating synthetic data via generative AI and adversarial training to enhance robustness under extreme conditions [25], ensuring that these technologies evolve from experimental tools to fair and life-saving solutions [26].

This shift from human-dependent, slow-response rescue methods to proactive, AI-driven ecosystems highlights the transformative potential of micromachine learning-drone systems. By addressing historical inefficiencies in speed, cost, and adaptability [27], they redefined disaster response models, enhancing resilience for the affected global population.

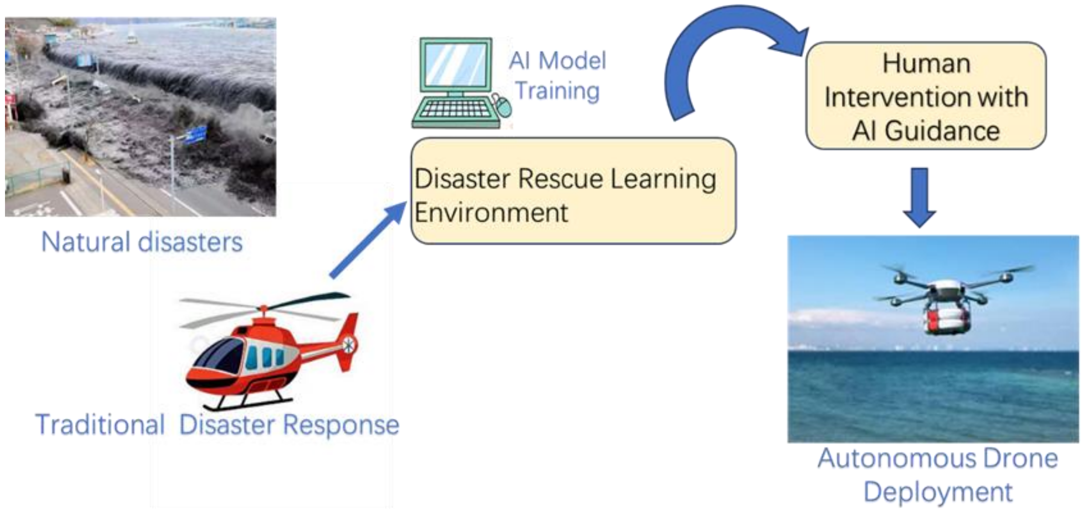

Figure 1.
Flowchart Overview.

3. Methodology

This study examines the application of TinyML in UAVs for disaster search operations, focusing on technical constraints and system optimization [28]. To ensure methodological rigor, the scope was intentionally limited to challenges specific to TinyML-UAV systems, excluding broader robotics or non-edge AI solutions.

The systematic literature search targeted peer-reviewed publications from 2020 to 2025 across four databases: ScienceDirect, Springer, Scopus, and IEEE Xplore [29]. These platforms were chosen for their comprehensive coverage of computer science and UAV research, including critical domains such as sensor fusion and swarm coordination [30] and edge computing.

This initial pool of 4,161 articles from databases such as IEEE Xplore, Springer, ScienceDirect, and Scopus, published between 2020 and 2025, was refined through a systematic selection process for TinyML drones. The PRISMA diagram in Figure 2 illustrates this methodology. Citation tracking of included papers identified additional studies, including 6G-enabled FANET architectures [31] and blockchain-secured edge computing, enhancing the review's comprehensiveness.

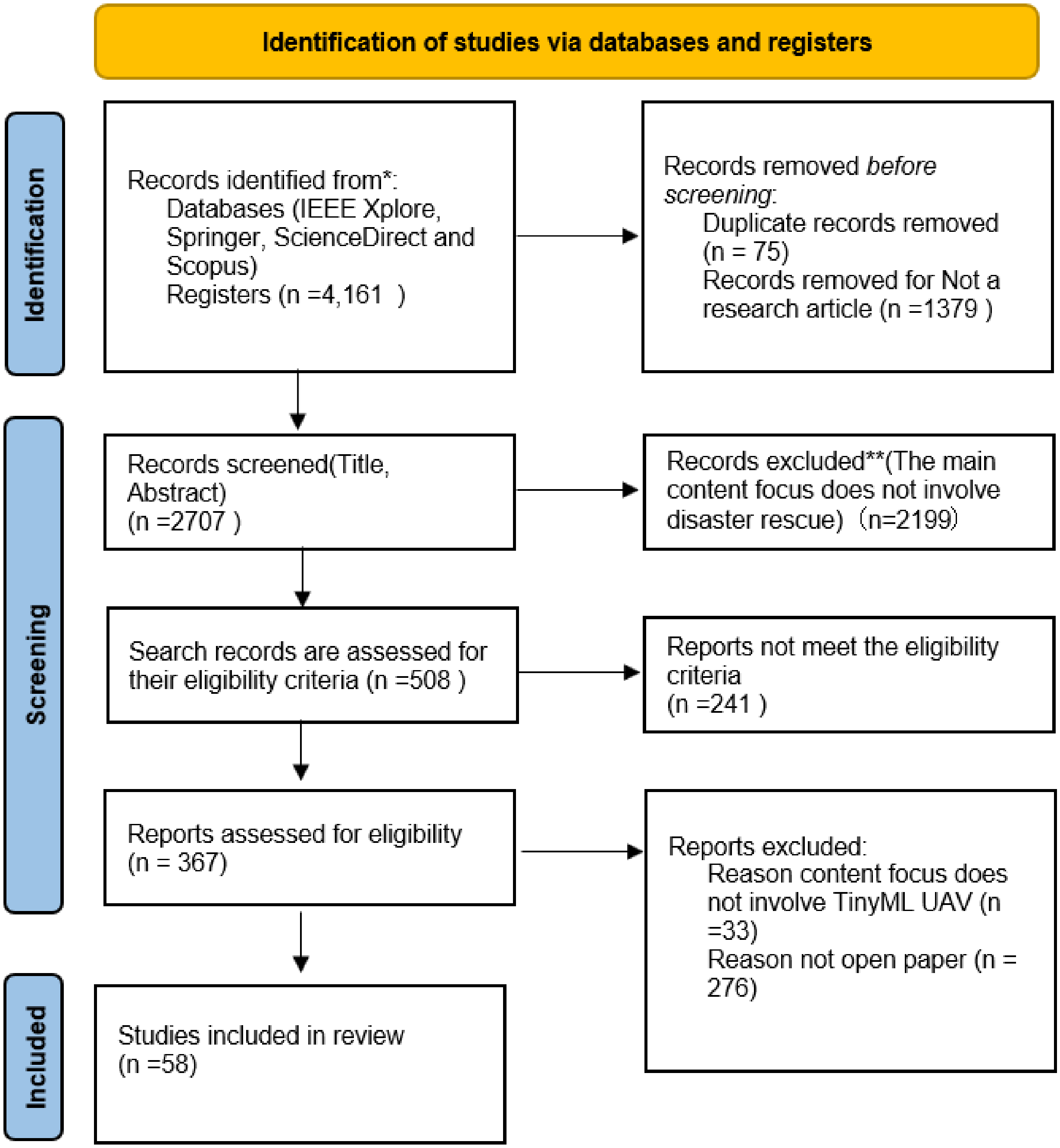

Figure 2.
PRISMA diagram.

The literature search strategy systematically integrated specific domain keywords related to three pioneering researchers in TinyML-UAV disaster response: Vijay Janapa Reddy (TinyML optimization), Daniela Rus (swarm robotics), and Roland Siegwart (autonomous navigation), as shown in the innovative framework in Figure 3.

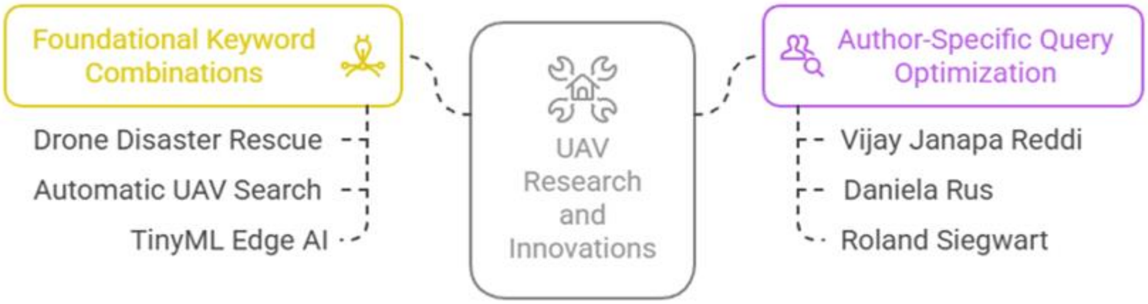

Figure 3.
UAV Research and Innovations in Disaster Scenarios.

"TinyML drones reflect Reddi's MLPerf Tiny benchmarks [32], focusing on energy-efficient edge AI for wildfire tracking and victim detection. This term highlights his NASA-collaborated work on standardized performance metrics for resource-constrained UAVs. "UAV disaster rescue" includes Rus's decentralized swarm algorithms [33], emphasizing self-healing networks for radiation mapping in Fukushima-like scenarios. The term highlights her research on ad hoc communication resilience in connectivity-limited zones. "TinyML automatic search" combines Reddi's edge computing frameworks with Siegwart's LiDAR-based 3D semantic mapping [34], targeting subcontinent precision in structural damage assessment during earthquakes. "Autonomous UAV search" integrates Siegwart's Airborne Disaster Assessment System (ADAS) [35] with Rus's dynamic path planning models, focusing on obstacle avoidance in urban debris fields. Citation chaining of pivotal works further identified advancements in ethical swarm governance [36] and modular UAV designs. This methodology ensures technical coherence while addressing scalability gaps, bridging hardware optimizations with real-world deployment challenges.

4. Literature Review Analysis: Current Approaches in UAV-Based Disaster Search and Rescue

A systematic analysis of publications from 2020 to 2025 revealed rapid evolution in the application of TinyML to UAV-based disaster search and rescue (SAR), characterized by conceptual breakthroughs, technical advancements, and ongoing challenges. Table 1 summarizes annual progress, emerging trends, and limitations in UAV-based disaster SAR technologies identified in the literature.

Table 1.
A Comprehensive Survey of Modern and Contemporary Representative Literature on the Development of Unmanned Aerial Vehicle (UAV) Disaster Relief Technology

	Core Concept	Key Advantages	Limitations
Aamer, et al. [3]	Autonomous navigation via hybrid neural networks	Adaptive path planning with top-down attention mechanisms	High computational load in dynamic environments
Yamamoto, et al. [4]	Multi-sensor fusion for night-time SAR	LiDAR + thermal imaging for low-light victim detection	High power consumption and sensor cost
Akhyar, et al. [8]	AI for disaster prediction & response	Predictive analytics for multi-hazard scenarios	Urban-centric training data biases
Chandran and Vipin [9]	FANET-based multi-UAV monitoring	Scalable coverage in connectivity-limited zones	Ad-hoc network latency (50-200ms)
Alnoman, et al. [11]	6G-enabled emergency localization	Sub-meter positioning accuracy	Requires 6G infrastructure (limited deployment)
Wang, et al. [20]	Deep learning obstacle avoidance	Real-time collision detection (YOLOv7)	GPU dependency (≥15W power draw)
Janapa Reddi, et al. [22]	TinyML frameworks for edge UAVs	<1W power consumption with ARM Cortex-M processors	15-30% accuracy loss after model compression
Lim, et al. [25]	Autonomous UAV for avalanche monitoring	Large-scale terrain mapping (5cm resolution)	-20°C battery capacity drops by 40%
Banbury, et al. [32]	MLPerf Tiny benchmarks	Standardized edge AI performance metrics	Trade-off: model size vs. inference speed
Talwandi, et al. [35]	Automated drone navigation systems	Cross-scenario compatibility	Limited real-time adaptability in debris fields
Rakshit, et al. [37]	Edge resource optimization (Righteous)	Dynamic model scaling for energy efficiency	Latency spikes under fluctuating task loads
Guo, et al. [38]	Task allocation via discrete PSO	89% coverage efficiency in simulated disasters	Scalability limits (>50 drones)
Talebkhah, et al. [39]	Edge-IoV task offloading	Federated learning for privacy preservation	Bandwidth constraints in rural areas
Heiss, et al. [40]	Thermal-motion fusion detection	92% accuracy in smoke/fog environments	Limited swarm coordination capability
Rohr, et al. [41]	Hybrid UAV dynamic control	GPS-denied precision landing (±5cm error)	Integration complexity with legacy systems
Zhang, et al. [42]	Multi-objective path planning	Warehouse inventory optimization (30% faster)	High compute demand for real-time replanning

Recent advancements in UAV technologies for disaster search and rescue (SAR) focus on improving autonomy, sensor integration, and operational scalability. The literature highlights three main methodologies: autonomous navigation with edge AI, multi-UAV swarm coordination, and multimodal sensor fusion, each providing unique benefits while facing ongoing limitations.

4.1. Autonomous Navigation and Real-Time Edge Processing

One of the core directions in current research is deploying lightweight artificial intelligence models on unmanned aerial vehicle (UAV) platforms to support real-time decision-making in dynamic environments. Studies have shown that autonomous navigation systems based on TinyML architectures can achieve low-latency, adaptive path planning, and obstacle avoidance in complex disaster scenarios [3, 35]. For instance, such systems have been successfully applied in maritime search and rescue missions, where a variant of the YOLOv7 model, compressed to run on processors consuming less than 1 watt, has enabled the automatic detection of individuals in water [43], significantly enhancing emergency response efficiency. Edge computing reduces power consumption and communication dependency. However, in visually challenging environments like heavy smoke or rain, the performance of these models can still decline considerably, despite their benefits. Literature [44, 45] indicates that detection accuracy may decrease by 15% to 30%. Additionally, due to the computational limitations of embedded hardware, deploying high-resolution models directly is challenging, necessitating a trade-off between detection accuracy and energy efficiency in system design. These issues underscore the urgent need for lightweight neural network architectures that are both efficient and robust to environmental variations.

4.2. Swarm Intelligence and Distributed Task Allocation

In large-scale disaster response, multi-UAV systems based on swarm intelligence have become a research focus. The ability of these algorithms to achieve efficient collaborative operations through bioinspired methods has attracted widespread attention. Studies have shown that using bioinspired techniques such as discrete particle swarm optimization (PSO) and integration with the flight ad hoc network (FANET) architecture [9, 46] can effectively coordinate UAV swarms, achieving up to 89% area coverage efficiency in simulated disaster scenarios. This significantly surpasses the operational capabilities of single-UAV systems. Such systems improve search efficiency and response speed by dynamically allocating tasks, such as thermal imaging reconnaissance and communication relay, among networked UAVs. However, as the swarm size increases, the system's scalability faces severe challenges: communication delays in FANETs typically range from 50 to 200 milliseconds, and the risk of synchronization failure increases, especially in environments where GPS signals are absent [47]. Additionally, to ensure real-time control performance, most swarm architectures must reduce environmental mapping resolution, compromising perception accuracy. Future research should focus on developing more reliable low-latency communication protocols and robust decentralized control mechanisms to achieve high-precision, stable, large-scale UAV collaboration.

4.3. Multimodal Sensor Fusion for Environmental Adaptability

The integration of heterogeneous sensors, such as lidar, thermal imaging cameras, and acoustic detectors, has become a key technical approach to overcoming the limitations of single-sensor perception and enhancing adaptability in complex environments [48]. Research indicates that such fusion frameworks significantly improve target detection capabilities under low-visibility conditions, especially in scenarios with obstructed views, such as night search and rescue or post-earthquake debris. For example, unmanned aerial vehicle (UAV) systems that combine thermal imaging and motion sensing data can more effectively identify survivors in smoke-filled wildfire areas, demonstrating their practical value in extreme disaster response. However, the collaboration of multiple sensors also results in a substantial energy burden. The increased sensor load directly leads to higher power consumption, reducing flight endurance and limiting continuous deployment in long-duration missions. Additionally, in harsh conditions such as heavy rainfall, electromagnetic interference, or extremely cold environments (e.g., subzero temperatures), sensor performance is susceptible to interference, decreasing reliability. These challenges underscore the urgent need to develop high-efficiency fusion algorithms and more environmentally robust sensor hardware to achieve stable and sustainable multimodal perception capabilities.

4.4. Ethical and Regulatory Considerations

Although technological innovation dominates the literature, recent studies have increasingly emphasized unresolved ethical and operational obstacles [49]. AI-driven triage systems exhibit significant geographical bias because their training data are overly concentrated in urban environments [8], limiting their applicability in rural or underrepresented areas. Models trained on limited datasets in specific disaster scenarios may incorrectly prioritize rescue resources, leading to imbalanced responses [49]. Additionally, the "black box" nature of such systems undermines trust between rescue personnel and affected communities, increasing deployment resistance [50]. The regulatory aspect also faces significant challenges: inconsistencies in beyond-visual-line-of-sight (BVLOS) policies across different jurisdictions seriously impede the coordination and implementation of cross-border search and rescue missions, even when technical conditions are mature [9]. These issues indicate that relying solely on

ISSN: 2576-8484
Vol. 10, No. 1: 1177-1188, 2026
DOI: 10.55214/2576-8484.v10i1.11904

technological progress is insufficient to achieve fair and efficient disaster response; it is necessary to combine technological innovation with explainable AI design, data-inclusive governance, and cross-national regulatory coordination to build a truly reliable and intelligent rescue system.

4.5. Gaps and Future Directions

The integration of TinyML into UAV systems has revolutionized disaster search and rescue (SAR) operations, enabling real-time edge processing with minimal energy consumption [37]. Studies demonstrate that optimized AI models achieve low-latency victim detection while maintaining energy efficiency [51]. A critical advancement for time-sensitive missions involves autonomous navigation systems that reduce human intervention through adaptive path planning, as observed in disaster scenarios with complex debris fields [52]. However, these systems face trade-offs: model compression improves energy efficiency but compromises accuracy in visually challenging environments like smoke-filled zones or heavy rainfall [45]. Similarly, multi-UAV swarm architectures leverage bioinspired algorithms (e.g., discrete particle swarm optimization [38]) to improve coverage efficiency; however, scalability remains hindered by communication delays and synchronization issues in GPS-denied regions.

A critical limitation lies in the geographic and ethical biases embedded in current AI-driven systems. Training datasets skewed toward urban environments result in poor generalization for rural or underrepresented disaster contexts, as evidenced by misprioritized rescue efforts in specific regional disasters [50]. Regulatory fragmentation further complicates cross-border deployments, delaying missions despite their technical readiness. Trust deficits arise from opaque AI decision-making, particularly in high-stakes scenarios lacking transparent justification.

Future research must address these gaps through interdisciplinary solutions. Synthetic data generation via generative AI can simulate region-specific disasters to mitigate data scarcity and bias. Federated learning frameworks enable collaborative training while preserving data privacy, enhancing adaptability to local conditions [39]. Robustness in extreme environments may be improved through adversarial training [40], while dynamic sensor optimization algorithms could enhance adaptability to real-time conditions. Explainable AI modules, such as attention-based visualization tools, are essential for building trust among responders.

Sustainable deployment requires cost-effective designs and regulatory harmonization. Modular UAVs with renewable energy components [53] and energy-harvesting materials could extend operational endurance in resource-limited regions. Global standards for UAV interoperability and integrated satellite networks [31] would streamline cross-border missions and ensure connectivity in infrastructure-damaged zones.

In summary, while TinyML-UAV systems represent a paradigm shift toward proactive disaster response, realizing their full potential requires balancing technical innovation, ethical governance, and equitable access. Prioritizing adaptive, transparent, and low-cost solutions will bridge the gap between theoretical advancements and real-world impact [54], safeguarding vulnerable populations in increasingly challenging environments [41].

5. Conclusions

Embedding TinyML into unmanned aerial vehicle (UAV) systems has significantly advanced technological innovation in search and rescue missions, enabling devices to perform low-power, high-efficiency real-time intelligent processing at the edge. With the aid of lightweight AI models, multisource sensor fusion, and swarm collaboration mechanisms, the response capabilities and environmental adaptability of UAVs in complex disaster scenarios have been notably enhanced. However, the large-scale application of this technology is still constrained by multiple factors, including the uneven geographical distribution of training samples, the lack of unified regulatory standards across countries, and ethical issues arising from the lack of transparency in algorithmic decision-making. These factors collectively affect its wide and fair deployment. The findings of this study are highly consistent with existing research results, both highlighting the structural bias of artificial intelligence toward urban areas in emergency response and warning of the risks associated with the application of UAVs in the absence of regulations. To address these challenges further, this paper proposes several technical countermeasures: generating diverse training samples through generative AI to alleviate data bias, adopting federated learning models to protect sensitive information, and establishing explainable AI architectures to increase system credibility. The coordinated application of these methods not only responds positively to the academic initiative of building "context-aware rescue systems" but also involves conducting an in-depth examination of the feasibility of directly replicating and promoting the technology in underdeveloped regions. By integrating modular hardware design, adversarial training strategies, and cross-national policy coordination mechanisms, this study systematically analyzes the path for the sustainable and responsible expansion of edge intelligence. This systematic review not only validates the critical role of TinyML-enabled UAVs in saving lives during climate disasters but also establishes a core direction for future research: only by optimizing computational efficiency while fully considering the social equity dimension in the technology implementation process can the lives and basic dignity of vulnerable populations worldwide be effectively safeguarded.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Acknowledgments:

The authors sincerely thank UCSI University and their supervisors for their continuous support and encouragement in promoting scientific research and innovation. Without the facilities and academic environment provided under their guidance, this work would not have been possible.

Copyright:

References

[1] United Nations Office for Disaster Risk Reduction, "Global assessment report on disaster risk reduction 2023: Mapping resilience for the sustainable development goals. United Nations Office for Disaster Risk Reduction," 2023. https://doi.org/10.18356/9789210028301

[2] M. Ishiwatari, "Leveraging drones for effective disaster management: A comprehensive analysis of the 2024 Noto Peninsula earthquake case in Japan," *Progress in Disaster Science*, vol. 23, p. 100348, 2024. https://doi.org/10.1016/j.pdisas.2024.100348

[3] N. Aamer, S. Bhadula, H. Patil, S. Gurpur, and A. Verma, "TDA-SSNN: Efficient hybrid top-down attention Siamese sparrow neural network for automatic drone navigation," in *2024 4th International Conference on Sustainable Expert Systems (ICSES) (pp. 1596-1602). IEEE*, 2024.

[4] Y. Yamamoto, Z. C. Tang, K. Taguchi, and H. Tsuchiya, "Drone with multiple sensors for night-time search missions of disaster victims," in *2024 IEEE 19th Conference on Industrial Electronics and Applications (ICIEA) (pp. 1-6). IEEE*, 2024.

[5] T. Nguyen, H. Nguyen, and T. N. Gia, "Exploring the integration of edge computing and blockchain IoT: Principles, architectures, security, and applications," *Journal of Network and Computer Applications*, vol. 226, p. 103884, 2024. https://doi.org/10.1016/j.jnca.2024.103884

[6] M. S. Abdalzaher, M. Krichen, and F. Falcone, "Emerging technologies and supporting tools for earthquake disaster management: A perspective, challenges, and future directions," *Progress in Disaster Science*, vol. 23, p. 100347, 2024. https://doi.org/10.1016/j.pdisas.2024.100347

[7] M. Osman, Y. Xia, M. Mahdi, and A. Ahmed, "Hybrid VTOL UAV technologies: Efficiency, customization, and sector-specific applications," *Alexandria Engineering Journal*, vol. 120, pp. 13-49, 2025. https://doi.org/10.1016/j.aej.2024.12.087

[8] A. Akhyar *et al*., "Deep artificial intelligence applications for natural disaster management systems: A methodological review," *Ecological Indicators*, vol. 163, p. 112067, 2024. https://doi.org/10.1016/j.ecolind.2024.112067
[9] I. Chandran and K. Vipin, "Multi-UAV networks for disaster monitoring: Challenges and opportunities from a network perspective," *Drone Systems and Applications*, vol. 12, pp. 1-28, 2024. https://doi.org/10.1139/dsa-2023-0079
[10] M. S. Akbar, Z. Hussain, M. Ikram, Q. Z. Sheng, and S. C. Mukhopadhyay, "On challenges of sixth-generation (6G) wireless networks: A comprehensive survey of requirements, applications, and security issues," *Journal of Network and Computer Applications*, vol. 233, p. 104040, 2025. https://doi.org/10.1016/j.jnca.2024.104040
[11] A. Alnoman, A. S. Khwaja, A. Anpalagan, and I. Woungang, "Emerging AI and 6G-based user localization technologies for emergencies and disasters," *IEEE Access*, vol. 12, pp. 197877-197906, 2024. https://doi.org/10.1109/ACCESS.2024.3521005
[12] M. M. Kuglitsch *et al*., "AI to the rescue: how to enhance disaster early warnings with tech tools," *Nature*, vol. 634, no. 8032, pp. 27-29, 2024. https://doi.org/10.1038/d41586-024-03149-z
[13] N. Ejaz and S. Choudhury, "Computer vision in drone imagery for infrastructure management," *Automation in Construction*, vol. 163, p. 105418, 2024. https://doi.org/10.1016/j.autcon.2024.105418
[14] R. Dasari *et al*., "Integration of consumer electronics in precision agriculture using low-carbon wheat lodging drone images," *IEEE Transactions on Consumer Electronics*, vol. 71, no. 2, pp. 6924 - 6932, 2025. https://doi.org/10.1109/TCE.2025.3552301
[15] H. Zhu, M. Huang, P. Ji, F. Xiao, and Q.-B. Zhang, "Transforming the maintenance of underground infrastructure through Digital Twins: State of the art and outlook," *Tunnelling and Underground Space Technology*, vol. 161, p. 106508, 2025. https://doi.org/10.1016/j.tust.2025.106508
[16] S. Safie and R. Khairil, "Regulatory, technical, and safety considerations for UAV-based inspection in chemical process plants: A systematic review of current practice and future directions," *Transportation Research Interdisciplinary Perspectives*, vol. 30, p. 101343, 2025. https://doi.org/10.1016/j.trip.2025.101343
[17] A. Buchelt *et al*., "Exploring artificial intelligence for applications of drones in forest ecology and management," *Forest Ecology and Management*, vol. 551, p. 121530, 2024. https://doi.org/10.1016/j.foreco.2023.121530
[18] D. Fischer-Preßler, D. Bonaretti, and D. Bunker, "Digital transformation in disaster management: A literature review," *The Journal of Strategic Information Systems*, vol. 33, no. 4, p. 101865, 2024. https://doi.org/10.1016/j.jsis.2024.101865
[19] N. Shaukat *et al*., "Trustworthy ROS software architecture for autonomous drones missions: From RoboChart modelling to ROS implementation," in *2024 20th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA) (pp. 1-7). IEEE*, 2024.
[20] W. Wang, C. Wang, Y. Sun, and X. Yu, "Research on automatic obstacle avoidance and target tracking system for drones based on deep learning," in *2024 Second International Conference on Data Science and Information System (ICDSIS) (pp. 1-5). IEEE*, 2024.
[21] D. Dong, Z. Wang, J. Guan, Y. Xiao, and Y. Wang, "Research on key technology and application progress of rescue robot in nuclear accident emergency situation," *Nuclear Engineering and Technology*, vol. 57, no. 6, p. 103457, 2025. https://doi.org/10.1016/j.net.2025.103457
[22] V. Janapa Reddi *et al*., "Widening access to applied machine learning with TinyML," *Harvard Data Science Review*, no. 1, 2022. https://doi.org/10.1162/99608f92.762d171a
[23] G. G. Anagnostopoulos, P. Barsocchi, A. Crivello, C. Pendao, I. Silva, and J. Torres-Sospedra, "ORDIP: Principle, practice and guidelines for open research data in indoor positioning," *Internet of Things*, vol. 30, p. 101485, 2025. https://doi.org/10.1016/j.iot.2024.101485
[24] M. Maimour, A. Ahmed, and E. Rondeau, "Survey on digital twins for natural environments: A communication network perspective," *Internet of Things*, vol. 25, p. 101070, 2024. https://doi.org/10.1016/j.iot.2024.101070
[25] J. Lim *et al*., "Autonomous and efficient large-scale snow avalanche monitoring with an Unmanned Aerial System (UAS)," *EGUsphere*, vol. 2024, pp. 1-29, 2024. https://doi.org/10.5194/egusphere-2024-2728
[26] L. Hu, X. Yan, and Y. Yuan, "Development and challenges of autonomous electric vertical take-off and landing aircraft," *Heliyon*, vol. 11, no. 1, p. e41055, 2025. https://doi.org/10.1016/j.heliyon.2024.e41055
[27] I. Ahmed, M. Alqahtani, M. Asif, and M. Khalid, "The role of energy management technologies for cyber resilient smart homes in sustainable urban development," *Energy Strategy Reviews*, vol. 56, p. 101602, 2024. https://doi.org/10.1016/j.esr.2024.101602
[28] B. Yan, Y. Wei, S. Liu, W. Huang, R. Feng, and X. Chen, "A review of current studies on the unmanned aerial vehicle-based moving target tracking methods," *Defence Technology*, vol. 51, pp. 201-219, 2025. https://doi.org/10.1016/j.dt.2025.01.013
[29] A. A. Baktayan, A. T. Zahary, A. Sikora, and D. Welte, "Computational offloading into UAV swarm networks: A systematic literature review," *EURASIP Journal on Wireless Communications and Networking*, vol. 2024, p. 69, 2024. https://doi.org/10.1186/s13638-024-02401-4
[30] S. S. Bhat, S. G. Anavatti, M. Garratt, and S. Ravi, "Review of autonomous outdoor blimps and their applications," *Drone Systems and Applications*, vol. 12, pp. 1-21, 2024. https://doi.org/10.1139/dsa-2023-0052

[31] A. Rago *et al.*, "Multi-layer NTN architectures toward 6G: The ITA-NTN view," *Computer Networks*, vol. 254, p. 110725, 2024. https://doi.org/10.1016/j.comnet.2024.110725

[32] C. Banbury *et al.*, "Mlperf tiny benchmark," *arXiv preprint arXiv:2106.07597*, 2021. https://doi.org/10.48550/arXiv.2106.07597

[33] M. Schwager, D. Rus, and J.-J. Slotine, "Decentralized, adaptive coverage control for networked robots," *The International Journal of Robotics Research*, vol. 28, no. 3, pp. 357-375, 2009. https://doi.org/10.1177/0278364908100177

[34] A. Cramariuc *et al.*, "Semsegmap–3d segment-based semantic localization," in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 1183-1190). IEEE*, 2021.

[35] N. S. Talwandi, P. Thakur, and S. Khare, "An automatic navigation system for new technical advanced drones for different alpplications," in *2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT) (Vol. 5, pp. 736-741). IEEE*, 2024.

[36] C. A. T. Romero, J. H. Ortiz, L. C. Rodríguez Timaná, F. V. Varela, A. H. Aristizábal Montufar, and J. Gamboa-Cruzado, "FANET and MANET, a support and composition relationship," *Computers, Materials & Continua*, vol. 82, no. 2, pp. 1699-1732, 2025. https://doi.org/10.32604/cmc.2025.056400

[37] A. Rakshit, S. Reddy, R. Ramnath, A. Arora, and J. Boubin, "Righteous: Automatic right-sizing for complex edge deployments," in *2024 IEEE/ACM Symposium on Edge Computing (SEC) (pp. 15-28). IEEE*, 2024.

[38] H. Guo, Y. Zhou, J. Wu, and F. Weng, "Automated task allocation for multi-drone reconnaissance missions based on optimized discrete particle swarm optimization," in *2024 4th International Conference on Artificial Intelligence, Robotics, and Communication (ICAIRC) (pp. 555-559). IEEE*, 2024.

[39] M. Talebkhah, A. Sali, V. Khodamoradi, T. Khodadadi, and M. Gordan, "Task offloading for edge-IoV networks in the industry 4.0 era and beyond: A high-level view," *Engineering Science and Technology, an International Journal*, vol. 54, p. 101699, 2024. https://doi.org/10.1016/j.jestch.2024.101699

[40] E. A. Heiss, A. V. Kozyr, and O. O. Morozov, "Detection of dynamic object by multi-agent multicopter system based on thermal motion equivalent method," in *2024 6th International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency (SUMMA) (pp. 841-846). IEEE*, 2024.

[41] D. Rohr, O. Andersson, N. Lawrance, T. Stastny, and R. Siegwart, "Unified guidance and jerk-level dynamic inversion for accurate position control of hybrid uavs," *IEEE Transactions on Robotics*, vol. 41, pp. 708 - 728, 2024. https://doi.org/10.1109/TRO.2024.3502206

[42] Y. Zhang, X. Chen, and H. Wang, "Multi-objective path planning for warehouse robots considering task efficiency and energy consumption," *Robotics and Computer-Integrated Manufacturing*, vol. 64, p. 101954, 2020.

[43] J. Taipalmaa, J. Raitoharju, J. P. Queralta, T. Westerlund, and M. Gabbouj, "On automatic person-in-water detection for marine search and rescue operations," *IEEE Access*, vol. 12, pp. 52428-52438, 2024. https://doi.org/10.1109/ACCESS.2024.3386640

[44] A. N. Paxton and A. Verma, "New parallel decision fusion models for improving multiclass object detection in drone images," in *2024 IEEE 3rd International Conference on Computing and Machine Intelligence (ICMI) (pp. 1-7). IEEE*, 2024.

[45] X. Wu, T. Han, W. Zhang, F. Wang, A. Xu, and C. Gao, "Research on automatic target recognition of UAV power inspection image based on deep learning intelligent algorithm," in *2024 2nd International Conference on Artificial Intelligence and Automation Control (AIAC) (pp. 378-382). IEEE*, 2024.

[46] M. Zaid, M. Kadir, I. Shayea, and Z. Mansor, "Machine learning-based approaches for handover decision of cellular-connected drones in future networks: A comprehensive review," *Engineering Science and Technology, an International Journal*, vol. 55, p. 101732, 2024. https://doi.org/10.1016/j.jestch.2024.101732

[47] M. J. Almansor *et al.*, "Routing protocols strategies for flying Ad-Hoc network (FANET): Review, taxonomy, and open research issues," *Alexandria Engineering Journal*, vol. 109, pp. 553-577, 2024. https://doi.org/10.1016/j.aej.2024.09.032

[48] M. N. Mowla, D. Asadi, T. Durhasan, J. R. Jafari, and M. Amoozgar, "Recent advancements in morphing applications: Architecture, artificial intelligence integration, challenges, and future trends-a comprehensive survey," *Aerospace Science and Technology*, p. 110102, 2025. https://doi.org/10.1016/j.ast.2025.110102

[49] U. Lagap and S. Ghaffarian, "Digital post-disaster risk management twinning: A review and improved conceptual framework," *International Journal of Disaster Risk Reduction*, vol. 110, p. 104629, 2024. https://doi.org/10.1016/j.ijdrr.2024.104629

[50] A. A. Laghari, A. K. Jumani, R. A. Laghari, H. Li, S. Karim, and A. A. Khan, "Unmanned aerial vehicles advances in object detection and communication security review," *Cognitive Robotics*, vol. 4, pp. 128-141, 2024. https://doi.org/10.1016/j.cogr.2024.07.002

[51] X. Liu, S. Li, and Z. Xiang, "Distributed collaborative search for dynamically moving targets in unknown environments utilizing multiple UAVs," in *2024 China Automation Congress (CAC) (pp. 1225-1230). IEEE*, 2024.

[52] G. Du, T. Li, G. Cao, P. Li, X. Xu, and Y. Zhang, "Path planning of warehouse UAV automatic inventory under multi-objective constraints," in *2024 6th International Conference on Robotics, Intelligent Control and Artificial Intelligence (RICAI) (pp. 393-398). IEEE*, 2024.

[53] F. Sanfilippo, M. H. Zafar, T. Wiley, and F. Zambetta, "From caged robots to high-fives in robotics: Exploring the paradigm shift from human–robot interaction to human–robot teaming in human–machine interfaces," *Journal of Manufacturing Systems*, vol. 78, pp. 1-25, 2025. https://doi.org/10.1016/j.jmsy.2024.10.015
[54] P. S. Kudyba, Q. Lu, and H. Sun, "Bayesian optimization for fast radio mapping and localization with an autonomous aerial drone," in *2024 IEEE 100th Vehicular Technology Conference (VTC2024-Fall) (pp. 1-5). IEEE*, 2024.