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Damage Severity And Resource Allocation

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Abstract: This review article explores various strategies for assessing post-disaster damage and optimizing resources, focusing on artificial intelligence and machine learning techniques. The research explores attention-based models, Fully Convolutional Networks (FCNs), multi-objective optimization, semi-supervised semantic segmentation, U-Net, and applications of Q-learning. Each method demonstrates distinct advantages in improving the accuracy, speed, and efficiency of disaster response initiatives. Key aspects involve using aerial images to assess damage, enhancing flood mapping, and distributing resources through reinforcement learning. These developments provide crucial tools for managing crises, enabling swift and precise evaluations and decisions in aftermath scenarios.

Index Terms - Artificial Intelligence (AI), Machine Learning (ML), Post-disaster damage assessment, Resource allocation, Attention-based models, Fully Convolutional Networks (FCNs), U-Net, Q-learning, Deep Q-learning (DQN), Multi-objective optimization, Semantic segmentation, UAV imagery, Reinforcement learning, Disaster management, Meta-heuristic algorithms

I. Introduction

The review article emphasizes the essential role of modern technologies in managing disasters, particularly in assessing damage after a disaster and allocating resources. Emergency response units encounter significant challenges when addressing natural disasters such as earthquakes, floods, and hurricanes, requiring accurate and timely information to assess damage and allocate resources efficiently. Traditional methods for assessing disasters, usually entailing manual assessments or basic remote sensing techniques, are time-consuming, resource-intensive, and prone to errors.

The rise of artificial intelligence (AI) and machine learning (ML) over recent years has provided new opportunities for automating and improving disaster management practices. Employing these technologies, especially when combined with aerial imagery and other remote sensing information, can greatly enhance the effectiveness and accuracy of damage assessments. AI models such as Fully Convolutional Networks (FCNs), attention-driven techniques, and deep learning architectures like U-Net serve as powerful resources for detecting, classifying, and delineating areas impacted by disasters.

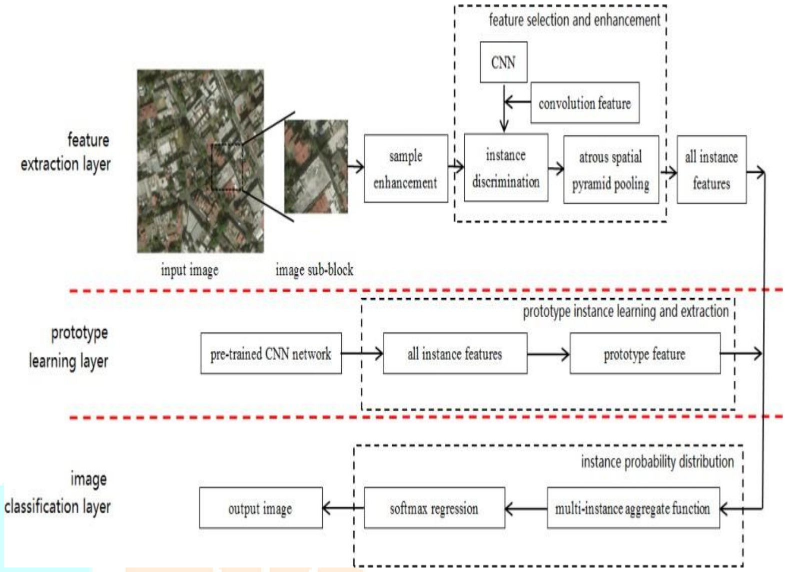
Moreover, utilizing machine learning methods like Q- learning and Deep Q-learning can improve the efficiency of disaster response through better resource allocation optimization. These approaches help leaders prioritize key areas and distribute limited resources in dynamic and complex environments.

This paper aims to evaluate and examine innovative AI and ML methods that are transforming the processes of post-disaster damage evaluation and resource optimization. It explores the use of these innovations in real-world scenarios and discusses their benefits, limitations, and possible methods to improve disaster response.

II. METHODOLOGY

2.1 Attention-Based Method

Chang Liu et al. [1] attention-based technique introduces a novel way to assess building damage after disasters using aerial imagery. Unlike traditional segmentation models, this approach integrates an attention mechanism to improve focus on relevant areas of an image. The model enhances its precision in categorizing damage levels by incorporating an attention layer that emphasizes significant features while



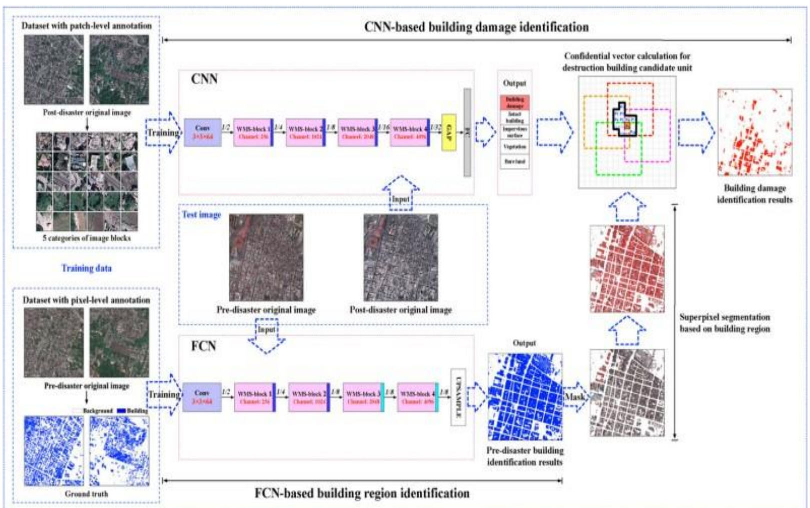
minimizing the impact of unrelated areas and noise. This is particularly beneficial in complex disaster situations where accurate and effective assessments are necessary.

Fig. 1. Proposed DMCNN model framework

The primary advantage of this method lies in its focus on categorization rather than complex segmentation, leading to improved computational efficiency. The attention mechanism helps the model focus on the essential parts of an image, avoiding distractions from less significant areas, which enhances classification accuracy. This efficiency renders the attention- centered model more appropriate for rapid assessments in disaster situations, facilitating swift and comprehensive evaluations of structural damage to support decision-making and resource allocation.

Future research on the attention-based model for post- disaster damage classification created by Liu et al. (2022) may focus on enhancing its adaptability to various disaster types, boosting its real-time assessment abilities, and integrating multiple data sources, like multispectral images, to improve precision. Although adaptive learning would allow the model to respond to new information, enhancing model interpretability would increase emergency responders' trust in AI-generated insights. Additionally, the widespread deployment of these models, especially in various real-world scenarios, could transform disaster response efforts by delivering more precise and beneficial assessments.

Research conducted by Wenfan Qiao and Edoardo Nemni demonstrates how Fully Convolutional Networks (FCNs) can assist in disaster evaluation for different emergencies through unique methodologies. Qiao et al.



[2] propose a technique for detecting building damage in high-resolution remote sensing images using minimal supervision. Their method effectively employs FCNs to identify key features associated with structural damage, reducing the requirement for extensive labeled data. This is particularly beneficial in post-disaster scenarios where gathering data proves challenging due to limited resources.

Fig. 2. Overall framework of proposed methodology for building damage detection

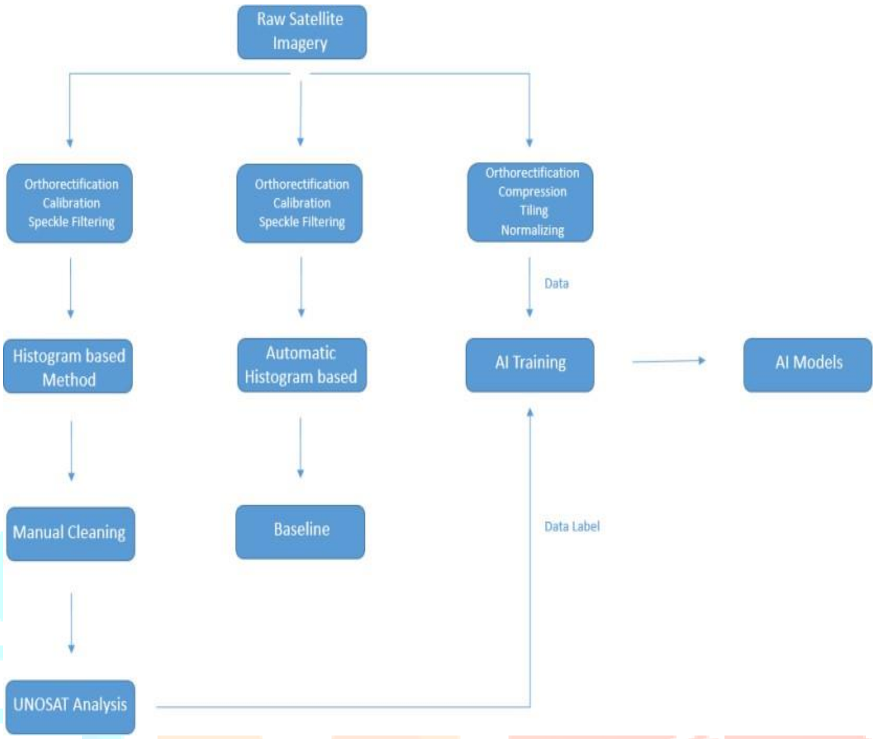


Fig. 3. Overview of our general workflow

Nemni et al. [3] focus on rapidly determining flood boundaries through a fully supervised FCN model, specifically employing Synthetic Aperture Radar (SAR) imagery. Their approach enables precise detection of flooded regions at the pixel level, which is crucial for rapid emergency response. SAR imagery is employed to ensure reliable detection in poor weather conditions or during nighttime, thus enhancing the accuracy and efficiency of flood assessments in important situations.

These studies highlight the versatility of FCNs in addressing diverse needs in disaster response. Qiao and his team demonstrate that weakly supervised learning can help simplify the evaluation of building damage, while Nemni and his group emphasize the quick and accurate flood mapping capabilities of FCNs. Both approaches illustrate the adaptability of deep learning techniques in leveraging various types of remote sensing data to improve disaster management strategies, whether evaluating structural integrity after a disaster or tracking floods in real-time. Through creative applications of FCNs, these researchers enhance the effectiveness of disaster response across different scenarios.

Future studies for the weakly supervised building damage detection model developed by Qiao et al. (2023) might concentrate on enhancing the model's versatility across a range of damage types and image characteristics, adding more data sources, such as LiDAR, to increase accuracy, and creating real-time processing for quick evaluations. The model's scalability and efficacy in responding to global disasters would be increased by testing it in a variety of situations and using continuous learning, which would enable the model to adjust with fresh disaster data. Future work on Nemni et al.'s (2020) flood segmentation model might concentrate on improving its resilience in various geographical areas, incorporating optical imaging for increased precision, and incorporating real-time processing for quicker reactions. The model's scalability for worldwide flood monitoring would be enhanced by adaptive learning, which would assist it in evolving with new SAR data.

2.2 Multi-objective optimization

Feiyue Wang et al. [4] effectively demonstrate the incorporation of multi-objective optimization in allocating resources post-disaster. Wang and colleagues utilize a Multi-Objective Cellular Genetic Algorithm to address the challenges of allocating resources over various timeframes. This method takes into account different goals that are in competition, like reducing recovery time and increasing resource utilization, ultimately improving decision-making in emergency situations. Jingran Sun and colleagues [5] focus on the longevity of interconnected infrastructure systems. Their model emphasizes the significance of acknowledging these connections to ensure that resource allocation is both effective and efficient. By boosting the overall resilience of impacted communities and systems, their approach improves coordination in disaster response by taking into account the interactions between various infrastructure systems. Multi-objective optimization allows for a balanced assessment of competing requirements, focusing on interrelations for a comprehensive understanding of re- source impacts on related systems. This cooperative approach enhances the effectiveness of emergency response initiatives, guaranteeing that resources are allocated to maximize recovery and lessen the effects of disasters. When utilized together, these frameworks provide valuable insights and approaches for improving resilience and optimizing resource allocation in post-disaster scenarios.

Possible directions for additional research on Feiyue Wang et al.'s (2020) cellular genetic algorithm for emergency re- source allocation involve improving adaptability to changing disaster scenarios and integrating machine learning to boost predictive capabilities. Enhancing the effectiveness of resource allocation necessitates considering the preferences of various stakeholders and adjusting to evolving constraints. Addition- ally, testing the algorithm in various disaster situations and modifying it for real-world applications could improve its efficiency in managing emergencies.

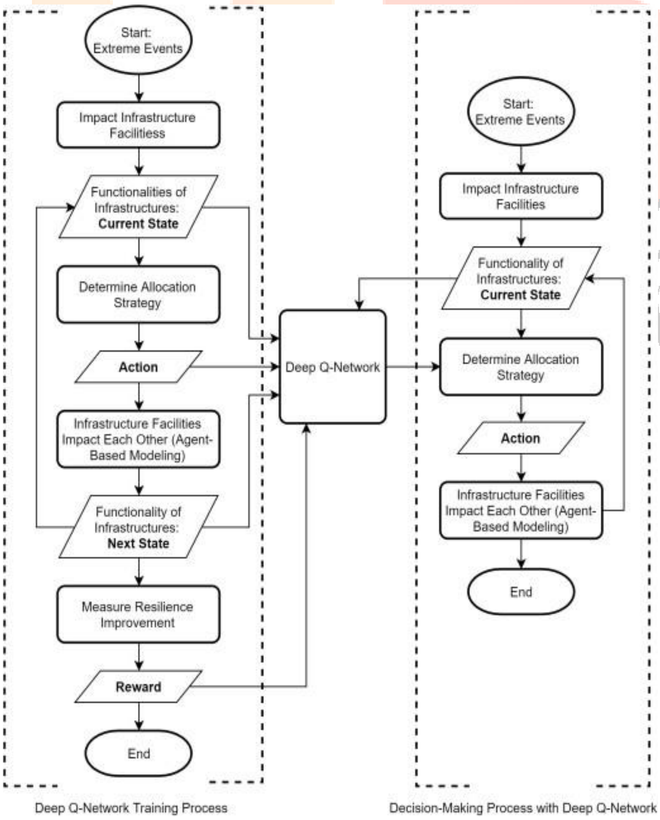


Fig. 4. Methodological Framework

Future research on the resource allocation framework by Jingran Sun et al. could improve flexibility across different infrastructure types and disasters, incorporate real-time data for faster responses, and take into account complex interrelations to bolster resilience. Employing machine learning can enhance the system's effectiveness in actual disaster scenarios by drawing insights from past events.

2.3 Semi-supervised Semantic Segmentation

Deepank Kumar et al. [6] utilize high-resolution aerial imagery along with semi-supervised transformers to effectively detect damaged areas in post-disaster scenarios. This method makes use of semi-supervised learning to tackle the problem of having a small amount of labelled data, which is a frequent obstacle in post-disaster situations. Transformers improve the analysis of high-resolution UAV data by capturing intricate spatial dependencies, resulting in more precise damage assessments.

Tashnim Jabir Shovon Chowdhury's dissertation delves into supervised and semi-supervised semantic segmentation methods for evaluating damage from natural disasters [7]. Supervised learning is employed when there is labelled data accessible, offering a strong method to train models effectively for precise classification of damage categories. The semi-supervised method expands on this ability by enabling the model to learn from both labelled and unlabeled data, enhancing scalability and adaptability, particularly in real-life emergency scenarios with limited labelled data.

Combined, these techniques provide unique benefits for evaluating damage after a disaster. Supervised learning achieves high accuracy in damage detection with plentiful labelled data, but semi-supervised learning offers more flexibility by using unlabeled data to enhance performance. The combination of precision and flexibility is essential for successful damage evaluation after disasters, enabling responders to make informed choices in efficiently distributing resources. Deepank Kumar et al. research utilizes ultra-high-resolution aerial images in combination with semi-supervised transformers for precise evaluation of post-disaster damage. Future work may broaden its application to different types of disasters, in- corporate real-time integration for faster decision-making, and enhance scalability and transferability for wider use. Including relevant information and dealing with ethical considerations would further improve its strength and justice. Chowdhury et al. propose further research to enhance the flexibility of models during various disasters, incorporate up-to-date data for quicker responses, enhance scalability, and incorporate multimodal data for improved precision. Developing semi- supervised techniques further and dealing with ethical issues could also guarantee equitable, extensive usage.

2.4 Dual-View Convolutional Neural Network (DV-CNN) model

The DV-CNN model improves disaster-damage classification by combining characteristics from two different perspectives of a damaged building. In situations after a flood, this two-perspective method greatly enhances the model's capability to identify subtle variations in levels of damage by combining characteristics from various viewpoints. The model takes features from each view separately using convolutional layers and then merges them, resulting in a more detailed and informative feature representation. This guarantees that any overlooked information in one perspective can be captured in another, enhancing the precision of damage categorization, crucial for efficient disaster response.

Along with dual-view image fusion, Luyuan Wu et al. integrated a Concentration-Based Attention Module into the DV-CNN design [8]. This mechanism assists the model in concentrating on the most crucial parts of the images, improving the classification process by emphasizing the most important regions. The model's ability to accurately classify buildings into different damage levels (slight, moderate, severe) is strengthened by integrating dual-view fusion and attention mechanisms, resulting in an efficient tool for real- time post-disaster damage assessment.

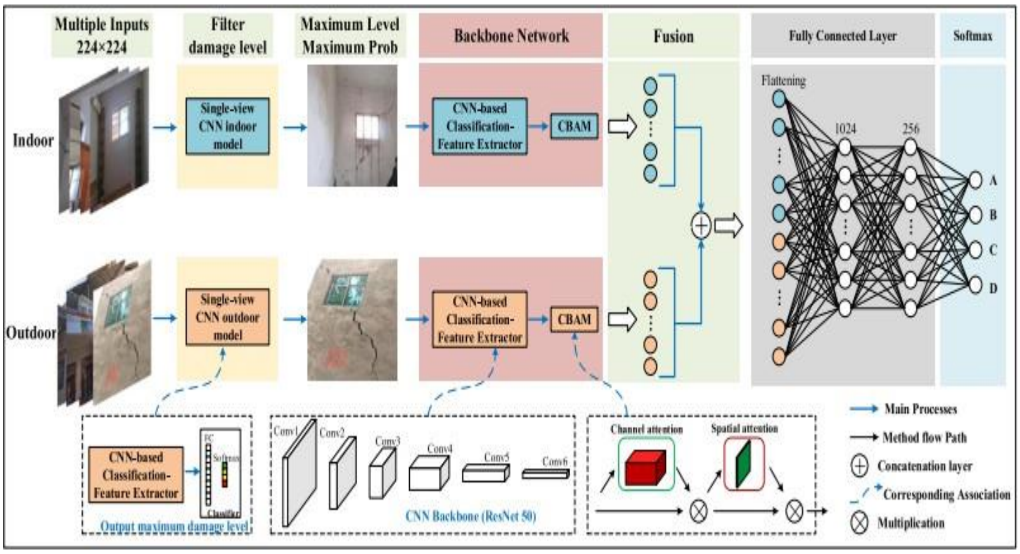


Fig. 5. The proposed architecture diagram of DV-CNN

Luyuan Wu et al. introduce a dual-view convolutional neural network that improves disaster damage classification by combining characteristics observed from both aerial and ground- level viewpoints. This method enhances the identification of minor changes in damage following floods by combining data from various perspectives. Moreover, the model is equipped with a Concentration-Based Attention Module that allows it to prioritize important image areas, enhancing the classification procedure. By combining these techniques, the DV-CNN can accurately sort buildings into categories of slight, moderate, or severe damage, making it a useful tool for immediate post-disaster evaluation. Chowdhury et al. (2024) investigate supervised and semi-supervised segmentation techniques for evaluating disaster damage. Future research could enhance the model's flexibility for different types of disasters, incorporate live data for quicker reaction, and boost scalability. Improving accuracy can be achieved by incorporating multimodal data and enhancing semi-supervised methods, while also addressing ethical concerns and bias to ensure fair application.

2.5 U-Net

To conduct a successful evaluation of building damage after a disaster, we can combine essential methods from three important research studies. Berezina et al. [9] utilize interconnected CNNs to examine images before and after disasters, enabling the model to detect changes in buildings over time, including collapsed roofs and debris, crucial for precise evaluation of damage. This method guarantees that the model can recognize alterations that are detectable only by directly comparing images before and after an event.

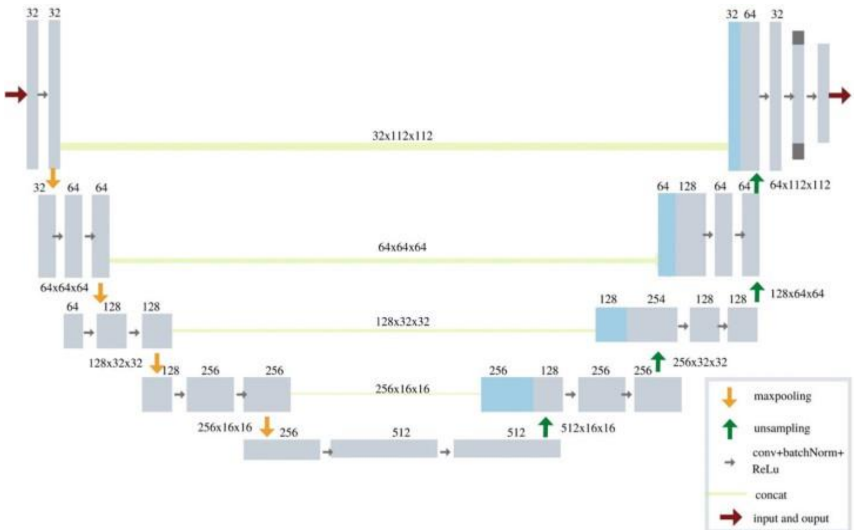


Fig. 6. U-Net model architecture for the building footprint segmentation problem

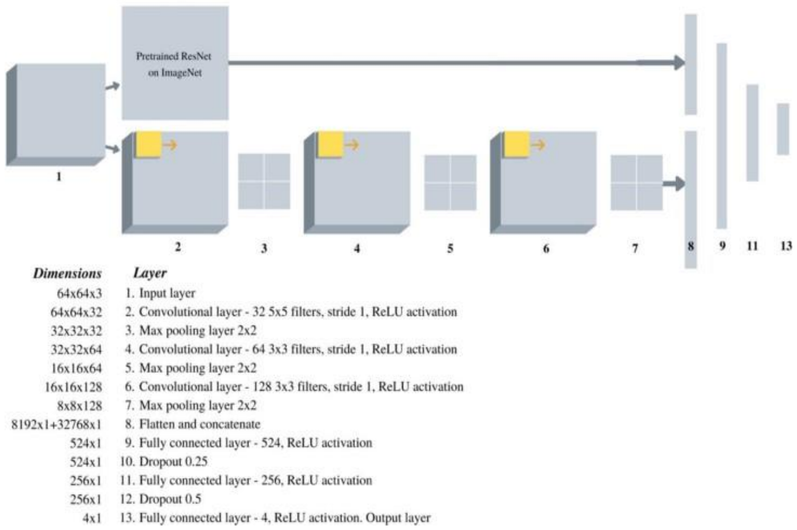


Fig. 7. Architecture of the damage classification model

Deng et al. enhanced U-Net plays a vital role in accurately segmenting areas of damage for semantic segmentation [10]. By incorporating attention mechanisms and multi-scale feature extraction, the upgraded U-Net boosts the model's precision in identifying disaster-affected areas and classifying various levels of damage. This leads to intricate damage maps, which enhance the model's ability to detect different levels of building damage.

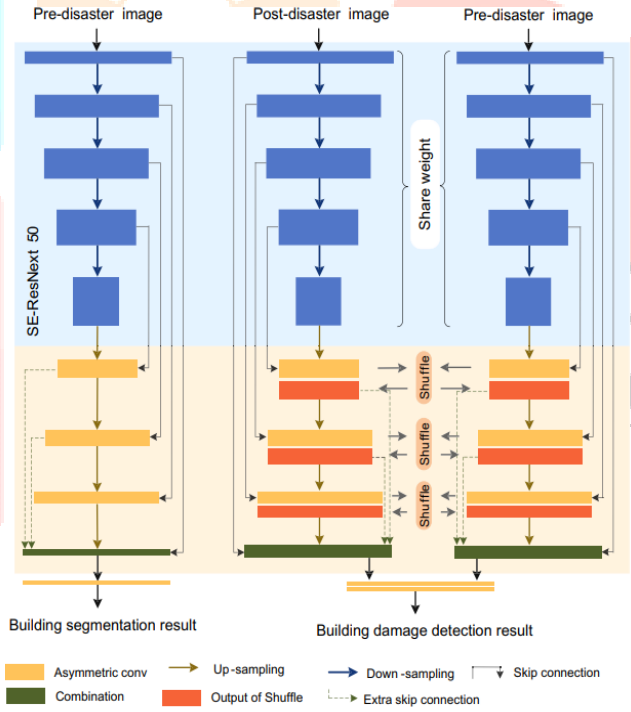


Fig. 8. Building damage assessment framework

Additional enhancement is provided by Zhonghua Hong et al., who present a new CNN specifically created for the classification of building damage [11]. This Convolutional Neural Network (CNN) can be utilized following the segmentation by U-Net to classify buildings into various levels of damage (such as undamaged, minor, moderate, or severe). By merging U-Net's segmentation skills with CNN's classification power, the method delivers detailed mapping and precise damage classification.

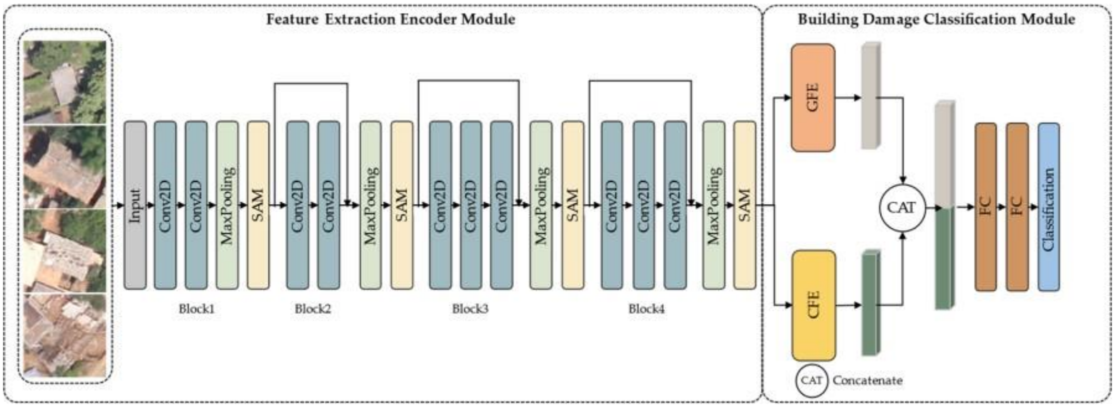


Fig. 9. The framework of the proposed EBDC-Net

A cohesive system that analyzes both pre- and post-disaster photos with connected CNNs, utilizes the enhanced U-Net for detailed segmentation, and employs a specialized CNN for classifying damage, provides a thorough and reliable approach for evaluating post-disaster damage. This method works well for major disaster events like Hurricane Michael, where precision and efficiency are crucial for response and recovery.

Deng et al. (2022) optimize building damage evaluation using an upgraded U-Net model. Future tasks could broaden the application of this technology to different types of disasters, incorporate live data for quicker reactions, and enhance its scalability. Including various types of data and improving effectiveness could boost precision, while tackling ethical concerns and biases would guarantee impartial use. Hong et al. (2022) suggest a CNN that can classify building dam- age through aerial images. Future plans involve modifying the model for different types of disasters, incorporating live data to improve response time, and expanding its reach to cover bigger regions. Enhancing accuracy and fairness can be achieved by incorporating multimodal data and addressing ethical considerations. Berezina et al. (2022) employ CNNs to evaluate hurricane destruction. Future plans involve modifying the model for various types of disasters, incorporating current data, enhancing scalability, and including multiple forms of data for better accuracy. Dealing with ethics and bias would promote equitable uses.

2.6 Q learning

Jayakumar et al research on Distributed Resource Optimization Using Q-learning, Q-learning [12] is utilized to improve resource allocation in device-to-device (D2D) communication networks. The objective is to improve decision-making in a de- centralized setting by enabling devices to independently learn how to efficiently share resources for better communication quality and less interference.

Effective Deep Q-Networks (EDQN) by Talaat et al. [13] enhances Q-learning by integrating deep learning within a deep Q-network. This blend enables the model to manage bigger state spaces, enhancing its efficiency for tasks involving dynamic resource allocation. EDQN employs neural networks to estimate Q-values, which is advantageous when there are a large number of state-action pairs to store explicitly.

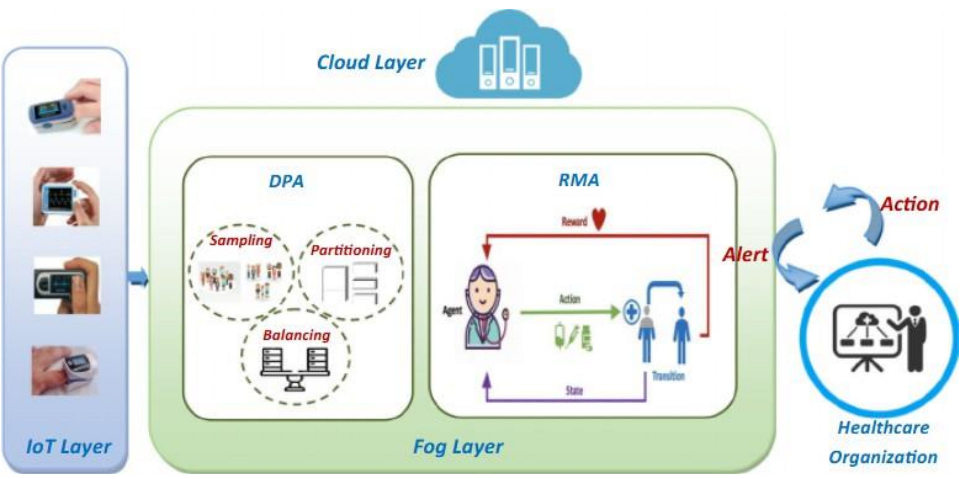


Fig. 10. Effective Resource Allocation Strategy (ERAS)

Both studies employ reinforcement learning for optimization tasks, however, they utilize distinct versions of Q-learning to reach their objectives. Q-learning focuses on enhancing local device interactions in D2D communication, while the EDQN method focuses on utilizing deep reinforcement learning for more intricate and dynamic decision-making.

Future developments for Jayakumar et al. (2024) may include enhancing scalability for bigger networks, integrating sophisticated reinforcement learning techniques such as deep Q-learning, and utilizing the model in various communication scenarios like 5G and IoT. Investigating ethical concerns and prejudices in distributing resources could also contribute to equitable, practical implementations. In the future, Talaat et al. (2022) could broaden the EDQN strategy to tackle larger and more intricate resource allocation issues, incorporate more advanced reinforcement learning methods for flexibility, and implement it in areas such as IoT. Dealing with ethical concerns and prejudice can help ensure equitable use.

2.7 Meta-heuristic algorithms

In the past few years, meta-heuristic algorithms have become widely used in addressing challenging, extensive optimization problems, specifically in disaster management and resource allocation. These algorithms are created to effectively navigate large solution spaces and prevent getting stuck in local optima by incorporating stochastic or population-based search methods. An important instance is the hybrid meta-heuristic strategy introduced by Nayeri et al.2023[14], aimed at reducing the time of deprivation in emergency resource planning by taking into account the impact of fatigue on rescue teams. The hybrid approach combines Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), with GA providing strong search abilities and PSO adjusting solutions using swarm behavior, optimizing resource allocation and scheduling in changing environments.

The progress in this area is demonstrated by Jain et al. use of combinatorial optimization for allocating emergency resources after disasters [15]. Their approach uses meta-heuristics to reduce response times and oversee the intricate allocation of scarce resources in impacted regions. By prioritizing the effective management of complex problems, this method guarantees that vital resources are quickly delivered to where they are needed, thus enhancing the overall efficiency of disaster relief efforts.

In resource management, Ghanbari et al. introduced the Ordered Weighted Averaging (OWA) approach to improve decision-making in uncertain situations [16]. This approach enables decision-makers to strike a balance between ideal and worst-case situations, ensuring that resources are distributed with efficiency and resilience in consideration. OWA is especially advantageous in chaotic crisis situations, in which the need for resources can quickly and unexpectedly change.

A comprehensive hybrid model can be created to tackle the complex challenges of post-disaster resource allocation by combining GA and PSO for optimal resource scheduling, combinatorial optimization for resource distribution, and OWA for robust decision-making. This approach offers a versatile and responsive solution that can adjust to changing disaster situations, reducing delays and taking into consideration the capabilities of rescue teams.

Nayeri et al. (2023) could enhance the algorithm to address various emergencies, incorporate real-time data for flexible planning, and enhance scalability in future research. Ensuring fairness in how resources are distributed would guarantee fair implementations. Jain et al. (2022) could further develop the optimization model to cover more disaster types, increase flexibility for allocating resources in real-time, and enhance scalability for larger disaster areas in future research. Incorporating advanced meta-heuristics and taking into account fairness in distributing resources would improve its practical utility. Potential future directions for Ghanbari et al. (2020) include utilizing the OWA-based meta-heuristic method in various crisis situations, enhancing flexibility for changing resource requirements, and ameliorating scalability for handling bigger crisis zones. Incorporating live data and enhancing equity in allocating resources would enhance its effectiveness.

3.2 Deep Q-Learning

Zhao et al. (2023) and Giri et al. (2023) utilize Deep Q- learning (DQN) for resource optimization in various scenarios. DQN improves conventional Q-learning by employing deep neural networks to estimate Q-values, enabling efficient management of large and complicated environments. In the research by Xianli Zhao and Guixin Wang [17], DQN is applied to enhance the scheduling of emergency resources for urban public health events, like pandemics or other emergencies. The model adapts its allocation of scarce medical resources like equipment and staff according to changing priorities. Through effective resource allocation, DQN enhances the timely delivery of medical supplies to areas with high demand, ultimately enhancing the overall response to health crises.

Giri et al. (2023) employ DQN in cognitive radio net- works to achieve optimal allocation of spectrum and energy resources [18]. In cognitive radio networks, intelligent resource allocation is necessary for maintaining efficiency when devices share the spectrum and manage energy from environmental harvesting. DQN is employed to understand the best distribution tactic, taking into account fluctuating energy levels and spectrum use, allowing for improved communication with reduced interference.

In both research projects, utilizing DQN assists in overcoming the constraints of conventional Q-learning, specifically in dealing with extensive state spaces. DQN uses neural networks to efficiently learn optimal policies in environments that are too complicated for tabular methods. DQN's blend of deep learning and reinforcement learning offers a strong tool for decision-making in intricate, evolving systems, whether it's in handling public health resources or enhancing communication networks.

Zhao et al. (2023) have the potential to broaden the Deep Q networks-based optimization approach to diverse public health emergencies, incorporate real-time data for flexible scheduling, and improve scalability for large urban areas in their future research. Studying more advanced reinforcement learning techniques and ensuring fairness in resource distribution would help encourage wider and fairer use. Future research for Giri et al. (2023) may involve extending multi- agent deep recurrent Q-learning to different network types, enhancing scalability for bigger cognitive radio networks, and incorporating advanced reinforcement learning methods for increased adaptability in spectrum management. Enhancing real-world applicability would be improved by ensuring fair spectrum access and addressing ethical considerations.

III. CONCLUSION

The review paper emphasizes how artificial intelligence (AI) and machine learning (ML) technologies are transforming disaster management by improving post-disaster damage assessment and resource distribution. Examined techniques, including attention-based models, Fully Convolutional Net- works (FCNs), U-Net, and reinforcement learning methods, have demonstrated improvements in the accuracy, efficiency, and scalability of emergency response systems. These models enable better detection and categorization of disaster-affected areas using advanced neural networks and high-resolution aerial imagery. Approaches such as attention-based models and FCNs enhance the capability to concentrate on important aspects in elaborate disaster settings, guaranteeing precise damage identification while diminishing interference. Semi- supervised learning models show how to create scalable solutions despite having minimal labelled data, a common scenario in emergencies.

Additionally, the utilization of multi-objective optimization and reinforcement learning, such as Q-learning and Deep Q-learning, enhances the allocation of resources in intense situations. These models consider the intricacy of inter- connected systems and opposing goals, enhancing decision- making and guaranteeing a more efficient distribution of limited resources. Despite the notable progress in AI and ML for disaster response, the assessment recognizes specific hurdles including data accessibility, model resilience in various settings, and the necessity for additional practical, real-time applications. Future studies need to address these constraints and investigate hybrid approaches that combine the benefits of various methodologies to enhance scalability, precision, and effectiveness in disaster response.

REFERENCES

[1] Liu, C., Sepasgozar, S. M. E., Zhang, Q., & Ge, L. (2022). A novel attention-based deep learning method for post-disaster building damage classification. *Expert Systems with Applications*, **202**. [Online]. Available: https://doi.org/10.1016/j.eswa.2022.117268

[2] Qiao, W., Shen, L., Wen, Q., Wen, Q., Tang, S., & Li, Z. (2023). Revolutionizing building damage detection: A novel weakly supervised approach using high-resolution remote sensing images. Article **2298245**. [Online]. Available: https://doi.org/10.1080/17538947.2023.2298245

[3] Nemni, E., Bullock, J., Belabbes, S., & Bromley, L. (2020). Fully convolutional neural network for rapid flood segmentation in synthetic aperture radar imagery. *Remote Sens.*, **12**(16), 2532. [Online]. Available: https://doi.org/10.3390/rs12162532

[4] Wang, F., Pei, Z., Dong, L., & Ma, J. (2020). Emergency resource allocation for multi-period post-disaster using multi-objective cellular genetic algorithm. *IEEE Access*, **8**, pages. [Online]. Available: 10.1109/ACCESS.2020.2991865

[5] Sun, J., & Zhang, Z. (2020). A post-disaster resource allocation framework for improving resilience of interdependent infrastructure networks. Transportation Research Part D: Transport and Environment, **85**, 102455. [Online]. Available: https://doi.org/10.1016/j.trd.2020.102455

[6] Singh, D. K., & Hoskere, V. (2023). Post-disaster damage assessment using ultra-high-resolution aerial imagery with semi-supervised transformers. *Sensors*, **23**(19), 8235. [Online]. Available: https://doi.org/10.3390/s23198235

[7] Chowdhury, T. J. S. (2024). Supervised and semi- supervised semantic segmentation for natural disaster damage assessment. *ProQuest Dissertations & Theses, University of Maryland, Baltimore County*. [ProQuest ID: 31244159].

[8] Wu, L., Tong, J., Wang, Z., Li, J., Li, M., Li, H., & Feng, Y. (2024). Post-flood disaster damaged houses classification based on dual-view image fusion and concentration-based attention module. *Sustainable Cities and Society*, **103**, pages. [Online]. Available: https://doi.org/10.1016/j.scs.2024.105234

[9] Berezina, P., & Liu, D. (2022). Hurricane damage assessment using coupled convolutional neural networks: A case study of Hurricane Michael. Article, pages 414–431. [Online]. Available: https://doi.org/10.1080/19475705.2022.2030414

[10] Deng, L., & Wang, Y. (2022). Post-disaster building damage assessment based on improved U-Net. *Scientific Reports*, **12**, Article number: 15862. [Online]. Available: https://doi.org/10.1038/s41598-022-20114-w

[11] Hong, Z., Zhong, H., Pan, H., Liu, J., Zhou, R.,Zhang, Y., Han, Y., Wang, J., Yang, S., & Zhong, C. (2022). Classification of building damage using a novel convolutional neural network based on post-disaster aerial images. Sensors 22(15),5920. [Online]. Available: https://doi.org/10.3390/s22155920

[12] Jayakumar, S., & Nandakumar, S. (2024). Distributed resource optimization using the Q- learning algorithm in device-to-device communication: A reinforcement learning paradigm. *Results in Engineering*, **23**, 102462. [Online]. Available: https://doi.org/10.1016/j.rineng.2024.102462

[13] Talaat, F. M. (2022). Effective deep Q-networks (EDQN) strategy for resource allocation based on optimized reinforcement learning algorithm. Article, **81**, 39945–39961. [Online]. Available: https://doi.org/10.1007/s11042-022- 13000-0

[14] Nayeri, S., Tavakkoli-Moghaddam, R., Sazvar, Z., & Heydari, J. (2023). Solving an emergency resource planning problem with deprivation time by a hybrid metaheuristic algorithm. *Proceedings of the 15th IIEC Conference*. [Online]. Available: 10.22070/jqepo.2020.5379.1150

[15] Jain, S., & Bharti, K. K. (2022). A combinatorial optimization model for post-disaster emergency resource al- location using meta-heuristics. *Soft Computing*, **27**(106). [Online]. Available: https://doi.org/10.1007/s00500-022- 07176-8

[16] Ghanbari, A. A., & Alaei, H. (2020). Meta-heuristic algorithms for resource management in crisis based on OWA approach. *Applied Intelligence*, **51**(8).[Online]. Available: https://doi.org/10.1007/s10489-020-01808-y

[17] Zhao, X., & Wang, G. (2023). Deep Q networks- based optimization of emergency resource scheduling for urban public health events. Article, **35**, 8823–8832. [Online]. Available: https://doi.org/10.1007/s00521-022- 07696-2

[18] Giri, M. K., & Majumder, S. (2023). Distributed dynamic spectrum access through multi-agent deep re-current Q-learning in cognitive radio network. *Physical Communication*, **58**, 102054. [Online]. Available: https://doi.org/10.1016/j.phycom.2023.102054