Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

A Comprehensive Survey on AI-Driven Disaster Response and Assessment Enhanced by Photogrammetry

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***Abstract*—Natural disasters such as earthquakes, floods, landslides, cyclones, and wildfires continue to cause large-scale human, economic, and environmental losses worldwide. Rapid and accurate disaster response is critical to minimizing casualties and infrastructure damage; however, conventional disaster management systems often suffer from delayed information availability, fragmented data sources, and limited situational awareness.**

Recent advances in artificial intelligence (AI), deep learning, unmanned aerial vehicles (UAVs), and photogrammetry have enabled new paradigms for automated disaster response and assessment. AI-driven models can analyze large volumes of heterogeneous data, including social media text, images, and sensor streams, while photogrammetric techniques enable accurate three-dimensional (3D) reconstruction of disaster-affected areas from aerial imagery. The integration of these technologies provides both semantic understanding and spatial awareness, which are essential for effective emergency decision-making.

This survey presents an in-depth and structured review of AI-driven disaster response and assessment systems enhanced by photogrammetry. The survey systematically analyzes state-of-the-art research works focusing on multimodal disaster information extraction, open-world disaster classification, UAV-based photogrammetric 3D reconstruction, AI-based damage assessment, and optimization-driven decision support. Each research paper is examined in terms of objectives, system architecture, methodology, datasets, performance metrics, results, and limitations. Finally, the survey identifies critical research gaps and future directions toward developing scalable, real-time, and robust disaster response systems.

***Index Terms*—Disaster Response, Artificial Intelligence, Photogrammetry, UAV, Multimodal Learning, 3D Reconstruction, Damage Assessment, Decision Support Systems**

I. Introduction

Natural disasters represent one of the most significant global challenges, affecting millions of people each year and causing extensive damage to infrastructure and natural ecosystems. Events such as earthquakes, floods, landslides, hurricanes, and wildfires often occur with little warning and evolve rapidly, leaving limited time for effective response and mitigation. According to global disaster reports, the frequency and intensity of such events have increased in recent decades due to climate change, urban expansion, and environmental degradation.

Traditional disaster response mechanisms rely heavily on manual field surveys, emergency calls, and post-event reporting. These approaches are time-consuming, labor-intensive, and often infeasible in hazardous or inaccessible environments. Moreover, conventional systems lack the ability to process the vast amounts of heterogeneous data generated during disasters, including social media posts, UAV imagery, satellite data, and sensor streams. As a result, emergency responders often face information overload, delayed situational awareness, and suboptimal decision-making.

Artificial intelligence has emerged as a transformative technology capable of addressing these challenges. Deep learning models can automatically analyze images, videos, and text data to detect disaster events, assess damage severity, and identify urgent humanitarian needs. At the same time, UAV-based photogrammetry enables rapid acquisition of high-resolution aerial

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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imagery and generation of accurate 3D models of disaster-affected areas. These models provide spatial context that is critical for planning rescue operations, allocating resources, and assessing infrastructure damage.

The integration of AI-driven data analysis with photogrammetric 3D reconstruction represents a powerful paradigm shift in disaster response. By combining semantic insights from AI models with geometric and spatial information from photogrammetry, integrated systems can deliver comprehensive situational awareness in near real-time. This survey aims to provide a detailed and structured review of such systems, focusing exclusively on research works relevant to AI-driven disaster response and assessment enhanced by photogrammetry.

II. Background and Evolution of Disaster Response Systems

Disaster response and assessment have evolved significantly from manual, field-survey-based approaches to automated and data-driven systems. Early disaster management relied primarily on physical reconnaissance, direct reporting, and post-event analysis. These processes were slow, hazardous, and lacked the spatial coverage required to assess large-scale disaster impacts comprehensively.

With the emergence of remote sensing technologies, including satellite imagery and aerial photography, disaster assessment capabilities improved substantially. However, these approaches still involved significant processing delays and required specialized expertise for interpretation. The introduction of geographic information systems (GIS) further improved spatial analysis but remained constrained by data acquisition latency.

The proliferation of social media platforms marked a significant shift in disaster information dissemination. Affected individuals began sharing real-time updates, images, and videos from disaster zones, creating vast and heterogeneous data streams that contain valuable situational information. Extracting actionable intelligence from such noisy and unstructured data required the development of advanced AI-based processing techniques.

Simultaneously, advances in UAV technology enabled rapid deployment of aerial platforms in disaster-affected areas. When combined with photogrammetric processing, UAV imagery enables high-resolution 3D reconstruction of damaged environments, providing emergency responders with unprecedented spatial awareness. Recent progress in deep learning has further accelerated damage assessment by enabling automatic detection and classification of damage indicators from aerial imagery.

The integration of these technologies, namely AI-driven multimodal data analysis, UAV-based photogrammetry, and optimization-based decision support, represents the current frontier in disaster response and assessment research. This evolution motivates the systematic review presented in this survey.

III. Related Works

This section presents a detailed review of state-of-the-art research works in AI-driven disaster response and assessment enhanced by photogrammetry. The reviewed papers are organized thematically to cover multimodal disaster information extraction, UAV-based photogrammetric reconstruction, AI-based damage assessment, change detection, and decision support optimization.

A. *Multimodal Disaster Information Extraction*

The rapid growth of social media platforms and mobile technologies has transformed how information is generated and disseminated during disaster events. Individuals affected by disasters often share real-time updates, images, and videos through platforms such as Twitter, Instagram, and Facebook. These multimodal data streams provide valuable situational insights but are highly unstructured, noisy, and heterogeneous. Extracting actionable disaster intelligence from such data requires advanced AI-based multimodal learning techniques.

Multimodal disaster information extraction aims to jointly analyze textual and visual content to improve the accuracy, robustness, and reliability of disaster detection and assessment systems. Unlike unimodal approaches that rely solely on text or images, multimodal systems leverage complementary information across modalities, enabling better contextual understanding of disaster scenarios.

Z. Zou et al. [1] proposed a multimodal framework that combines both textual and visual information for disaster classification, addressing the inconsistent reliability of unimodal social media data. The primary objective of this work is to improve disaster image classification accuracy by leveraging complementary cues from social media text and images, focusing on real-time disaster monitoring scenarios where rapid identification of disaster types is crucial for emergency response. The proposed system architecture consists of four major components: data acquisition, feature extraction, multimodal fusion, and classification. Social media posts containing both images and accompanying text are collected as input data. Visual content is processed using a convolutional neural network (CNN) to extract high-level image features, while textual data is processed using word embedding techniques to capture semantic information. A late fusion strategy is employed to combine visual and textual feature representations, which are then fed into a classification module that predicts the disaster category, such as earthquake, flood, fire, or hurricane. The methodology involves preprocessing both image and text data to reduce noise and improve feature quality, with images undergoing resizing, normalization, and augmentation, and textual data cleaned through tokenization and removal of irrelevant symbols. The study utilizes a large-scale disaster-related social media dataset containing labeled images and textual descriptions across multiple disaster events. Experimental results demonstrate that multimodal fusion significantly outperforms unimodal baselines, achieving higher classification accuracy and improved generalization across different disaster categories. A key contribution of this work

International Journal of Engineering Research & Technology (IJERT)
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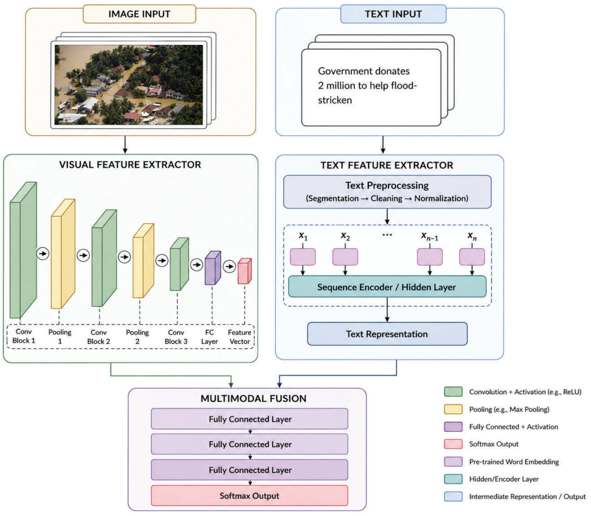

Fig. 1. Multimodal Social Media–Based Disaster Classification Architecture [1]

is demonstrating that even simple fusion strategies can yield substantial performance gains when applied to disaster-related social media analysis. Despite its effectiveness, the approach faces limitations related to data availability and quality, as not all social media posts contain both text and images, and model performance is sensitive to noisy or misleading content.

X. Yu et al. [2] addressed the critical limitation of closed-world disaster classification systems by introducing an open-world learning framework for multimodal social media data. Most existing disaster classification systems operate under a closed-world assumption where all possible disaster categories are known in advance; however, real-world disaster events are highly dynamic, and new or unseen disaster types may emerge that are absent from training datasets. The primary goal of this research is to enable disaster classification systems to identify unknown or novel disaster categories rather than misclassifying them as known events. The proposed architecture integrates multimodal feature extraction with an open-world classification mechanism, where textual data is encoded using transformer-based language models and images are processed using deep CNN architectures. A cross-modal attention mechanism aligns textual and visual representations, enabling effective multimodal fusion. The system employs a dual-classification strategy consisting of a closed-world classifier for known disaster categories and an open-world detector for samples that do not belong to any known class. To address the scarcity of unknown-class samples during training, the authors employ synthetic sample generation techniques such as manifold mixup, which helps the model learn decision boundaries that separate known and unknown categories. The system is trained using a combination of supervised learning for known classes and uncertainty estimation for open-world detection. Results indicate that the proposed framework significantly improves the model's ability to detect unseen disaster events compared to traditional closed-world classifiers, demonstrating

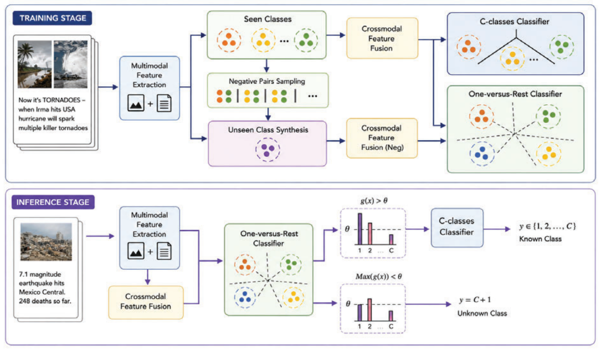

Fig. 2. Architecture for Open-World Disaster Information Identification [2]

robust performance across multiple disaster scenarios. The key contribution of this work lies in its explicit treatment of uncertainty and novelty in disaster classification. However, the primary limitation is increased computational complexity due to attention mechanisms and synthetic sample generation, and the framework relies on curated datasets that may limit generalization to highly noisy real-world data.

B. UAV-Based Photogrammetry for Disaster Assessment

Unmanned Aerial Vehicles (UAVs) have emerged as one of the most effective data acquisition platforms for disaster response due to their rapid deployability, flexibility, and ability to access hazardous or inaccessible areas. UAVs equipped with high-resolution cameras can capture detailed aerial imagery shortly after a disaster occurs, enabling timely assessment of affected regions. When combined with photogrammetric processing techniques, UAV imagery allows the generation of accurate three-dimensional (3D) models that provide essential spatial context for emergency response planning.

Photogrammetry involves extracting geometric information from overlapping images to reconstruct the three-dimensional structure of a scene. Modern photogrammetric pipelines typically rely on Structure-from-Motion (SfM) and Multi-View Stereo (MVS) techniques. These methods estimate camera poses, generate sparse and dense point clouds, and produce textured surface models. In disaster scenarios, photogrammetry enables quantitative analysis of structural damage, terrain deformation, and environmental changes, which are difficult to assess using conventional two-dimensional imagery. Despite its advantages, UAV-based photogrammetry faces several challenges in disaster environments, including limited flight time, unstable lighting conditions, occlusions, and the absence of reliable GPS signals. Recent research has focused on addressing these limitations by developing near real-time reconstruction pipelines and robust localization strategies.

Y. Cheng et al. [3] addressed the challenge of computationally intensive photogrammetric reconstruction workflows by proposing a low-latency incremental framework suitable for emergency applications. Traditional workflows often require hours or days to generate complete 3D models, which is unacceptable in disaster response scenarios where timely situational

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ISSN: 2278-0181
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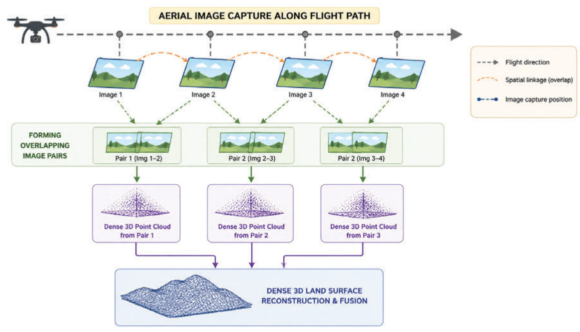

Fig. 3. Near-Real-Time Photogrammetric Reconstruction Workflow [3]

awareness is critical. The primary objective of this work is to enable incremental 3D reconstruction of disaster-affected areas as UAV imagery is being captured, rather than waiting for the complete dataset. The proposed system architecture is designed around a sequential image processing pipeline, where UAV images are captured in a temporal sequence and processed incrementally. A key component is the Spatially Linking Sequential Images (SLSI) mechanism, which selects valid image pairs for stereo matching based on spatial and temporal constraints. The pipeline includes feature extraction and matching, camera pose estimation using Perspective-n-Point (PnP), and sliding-window bundle adjustment to optimize recent camera poses. Dense reconstruction is performed using stereo matching algorithms, followed by triangulation and fusion to generate a gradually expanding 3D surface model. The methodology emphasizes computational efficiency, with processing times of a few seconds per image achieved using CPU-only implementations, enabling on-the-fly visualization of disaster-affected regions. Experimental results demonstrate that the proposed framework can generate 3D surface models with acceptable geometric accuracy while maintaining low latency, without relying on GNSS or inertial measurement units. The primary limitation is reduced accuracy compared to offline photogrammetric pipelines, and the system is sensitive to poor texture, limited overlap, and short baselines between images.

S. Ikeda et al. [4] addressed the challenge of UAV-based photogrammetry in environments where GPS signals are unavailable or unreliable, such as collapsed buildings, tunnels, underground structures, or dense urban areas. Conventional UAV photogrammetry workflows rely heavily on GPS for georeferencing and camera localization, limiting their applicability in such settings. The objective of this research is to develop a UAV-based photogrammetric workflow capable of achieving high-accuracy 3D reconstruction in GPS-denied environments. The system architecture integrates specialized UAV platforms equipped with vision-based navigation sensors and controlled illumination systems. Image acquisition is carefully planned to ensure high overlap and consistent lighting conditions, and ground control points (GCPs) are strategically placed to enable accurate scaling and validation of reconstructed models.

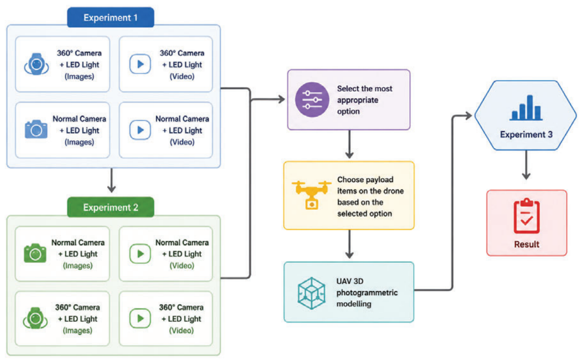

Fig. 4. Precision 3D Modeling Pipeline for GPS-Denied Disaster Scenarios [4]

Photogrammetric processing is performed using a standard SfM-MVS pipeline, followed by dense point cloud generation, mesh reconstruction, and texture mapping. The methodology involves extensive experimental validation in tunnel environments with varying lighting conditions and camera configurations. Results show that centimeter- to millimeter-level accuracy can be achieved under optimal conditions, demonstrating the feasibility of UAV photogrammetry in challenging disaster environments. The primary contribution is demonstrating that UAV-based photogrammetry can be reliably deployed in environments previously considered unsuitable for aerial mapping. Despite its accuracy, the approach requires significant setup effort, is not suitable for rapid large-scale disaster assessment, and the reliance on controlled environments and GCPs limits applicability in highly dynamic disaster scenarios.

C. AI-Based Damage Assessment and Change Detection

Accurate and timely damage assessment is a critical requirement in disaster response, as it directly influences rescue prioritization, resource allocation, and recovery planning. Manual inspection of affected areas is often slow, dangerous, and impractical at scale. Consequently, artificial intelligence–based damage assessment methods have gained significant attention in recent years, particularly those leveraging deep learning and UAV imagery. AI-based damage assessment systems aim to automatically identify damaged structures, classify severity levels, and detect changes in the built and natural environment. Compared to traditional image analysis techniques, deep learning models are capable of learning complex visual patterns associated with disaster damage, enabling more reliable and scalable assessment.

F. Kizilay et al. [5] addressed the need for automated, real-time damage detection from UAV imagery, as post-earthquake damage assessment traditionally relies on field surveys that can take days or weeks to complete. The objective of this research is to evaluate and compare multiple deep learning models for detecting and classifying earthquake-induced structural damage from aerial images. The system architecture consists of a UAV-based image acquisition module, a preprocessing

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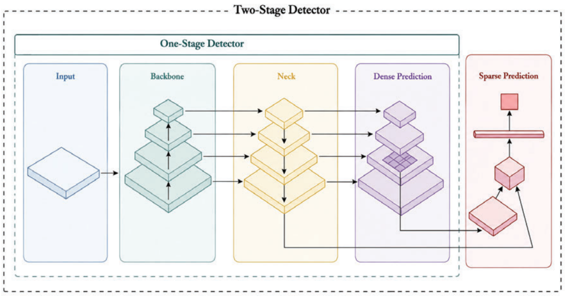

Fig. 5. Deep Learning–Based Earthquake Damage Assessment Pipeline [5]

pipeline, and a deep learning inference engine, evaluating multiple architectures including YOLO-based object detection models, region-based CNNs, and modified VGG-style classifiers. These models are trained to detect damage indicators such as cracks, collapsed walls, and debris, and to classify damage severity levels. The methodology employs transfer learning to adapt pre-trained models to earthquake damage datasets, with data augmentation techniques such as rotation, scaling, and illumination variation applied to improve model robustness. Experimental results demonstrate that YOLO-based models achieve superior performance in terms of both accuracy and real-time inference speed, capable of processing images in sub-second time, making them suitable for time-critical disaster response applications. The key contribution lies in demonstrating the feasibility of deploying deep learning–based damage assessment systems on UAV platforms for rapid post-earthquake evaluation. However, model performance is sensitive to image quality, occlusion, and extreme lighting conditions, and the approach focuses primarily on earthquake damage, requiring retraining for other disaster types.

S. Mineo et al. [6] proposed a multispectral photogrammetric approach for landslide monitoring that addresses the limitation of traditional methods failing to capture subsurface changes that precede landslide events. Landslides pose a significant risk to infrastructure and human safety, particularly in mountainous and coastal regions. The proposed system utilizes UAVs equipped with both RGB and thermal infrared cameras, with separate photogrammetric pipelines used to generate visible and thermal 3D models, which are subsequently aligned and fused. The fused models enable combined analysis of geometric deformation and thermal anomalies. The methodology involves multi-temporal data acquisition and comparative analysis of dense point clouds, where thermal anomalies are correlated with geometric changes to identify potential landslide activity. Experimental results demonstrate improved detection of landslide-prone zones compared to RGB-only approaches. The approach requires specialized sensors and increased processing complexity, and its applicability is limited by environmental conditions such as weather and vegetation cover.

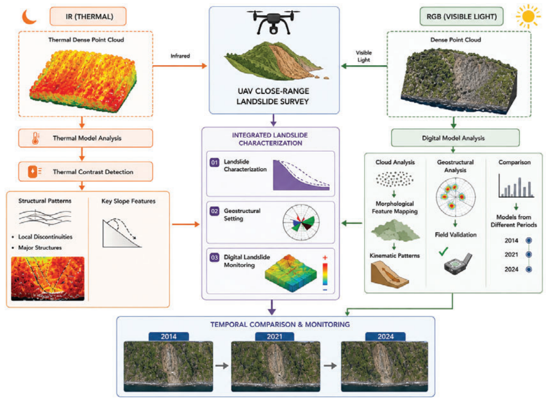

Fig. 6. Multispectral Photogrammetry-Based Landslide Assessment Framework [6]

D. Photogrammetry-Based Change Detection for Disaster Monitoring

Change detection techniques aim to identify differences between pre-disaster and post-disaster states to quantify damage and environmental impact. Photogrammetry-based change detection leverages multi-temporal aerial imagery and 3D models to analyze spatial changes over time. Compared to purely image-based approaches, photogrammetric change detection provides metric and spatially consistent measurements, which are essential for decision-making in disaster preparedness and early response planning.

S. Kögel et al. [7] addressed the need for automated and timely detection of changes in flood-prone areas, as conventional flood assessment approaches rely on post-event analysis, limiting their usefulness for proactive response and early warning. The primary objective is to develop a near real-time change detection framework that can identify meaningful geometric and surface changes from multi-temporal aerial imagery, thereby supporting flood preparedness and early response planning. The proposed system architecture consists of three main components: multi-temporal data acquisition, photogrammetric 3D reconstruction, and change detection analysis. Aerial images captured at different time instances are processed through a photogrammetric pipeline to generate comparable surface models or orthophotos, which are then aligned within a common reference frame. A change detection module computes differences in elevation, surface geometry, or texture, and the system includes visualization components that highlight detected changes for rapid interpretation by decision-makers. The methodology relies on multi-temporal UAV or aerial image datasets captured before and during flood events, with change detection carried out using distance metrics between corresponding surfaces and threshold-based filtering to isolate significant changes. Experimental results demonstrate that the proposed tool can detect relevant terrain and surface changes in near real-time, enabling early identification of flood-affected regions. The accuracy of change detection depends on the quality of image alignment and the availability of consistent multi-temporal data, and environmental factors such

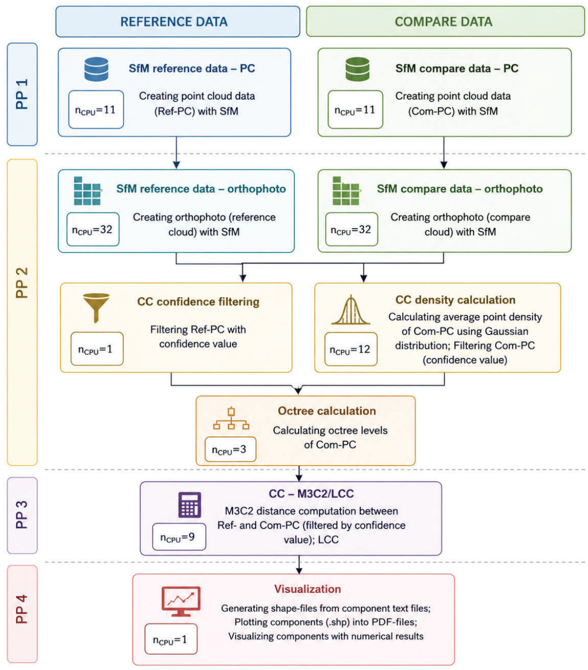

Fig. 7. Photogrammetry-Based Change Detection Framework for Flood Preparedness [7]

as vegetation movement and lighting variations can introduce false positives.

E. Infrastructure Damage and Deformation Monitoring

Critical infrastructure such as bridges and overpasses plays a vital role in transportation and emergency logistics during and after disaster events. Assessing structural integrity and detecting deformation are therefore essential components of post-disaster evaluation. UAV-based photogrammetry offers a non-contact and high-resolution alternative to traditional sensor-based monitoring techniques.

M. Maboudi et al. [8] addressed the need for high-resolution, non-contact deformation monitoring of bridge structures using aerial imagery, as traditional deformation monitoring techniques relying on ground-based sensors provide limited spatial coverage and require costly installation. The objective is to assess whether UAV-based photogrammetry can provide sufficient accuracy and spatial resolution to detect small-scale structural deformations. The system architecture consists of a UAV-based image acquisition module, a high-resolution photogrammetric reconstruction pipeline, and a deformation analysis module. UAVs capture overlapping images of bridge structures from multiple viewpoints, which are processed using an SfM-MVS pipeline to generate dense point clouds and surface models. A deformation analysis module then compares multi-temporal 3D models to estimate displacements and structural changes. The methodology involves repeated UAV surveys of bridge structures, with ground control points and reference measurements used to validate photogrammetric results, and deformation quantified

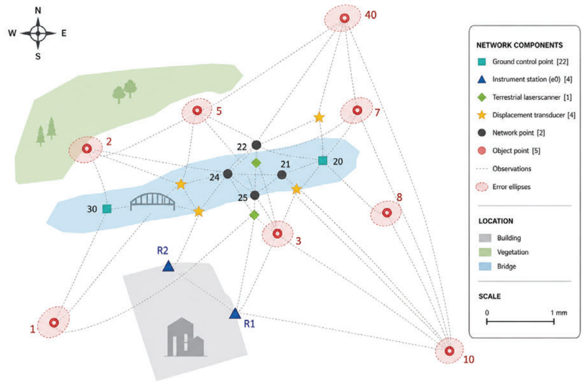

Fig. 8. UAV-Based Photogrammetric Pipeline for Bridge Deformation Monitoring [8]

by computing surface-to-surface differences between temporal models. Results indicate that UAV-based photogrammetry can achieve millimeter- to centimeter-level accuracy in deformation measurement, demonstrating its suitability for post-disaster infrastructure assessment. The approach requires careful flight planning and stable imaging conditions, and wind and lighting variations can affect reconstruction quality and measurement reliability.

F. Decision Support and Optimization in Disaster Response

Beyond damage detection, disaster response requires coordinated decision-making across multiple agencies and resource constraints. Decision support systems (DSS) aim to translate assessment outputs into actionable strategies for emergency management. Coordinating disaster response activities involves complex optimization problems, including resource allocation, task scheduling, and inter-agency coordination.

A. Author et al. [9] proposed an optimization-driven decision support system for coordinating disaster response, integrating a multi-agent framework with an improved genetic algorithm. Each agent represents an emergency response unit, and the genetic algorithm optimizes response strategies based on multiple objectives such as response time, resource utilization, and coordination efficiency. The improved genetic algorithm incorporates adaptive mutation and crossover strategies to enhance convergence. Simulation-based evaluation demonstrates significant improvements in response time and coordination efficiency compared to traditional approaches. The effectiveness of the system depends on the accuracy of input data and may degrade under highly uncertain conditions.

G. Multimodal Social Media–Based Disaster Assessment

Social media platforms generate large volumes of real-time data during disaster events, including textual descriptions and images posted by affected individuals. Multimodal deep learning aims to exploit the complementary nature of these data sources to improve disaster detection and assessment accuracy. Unimodal approaches that rely only on text or only

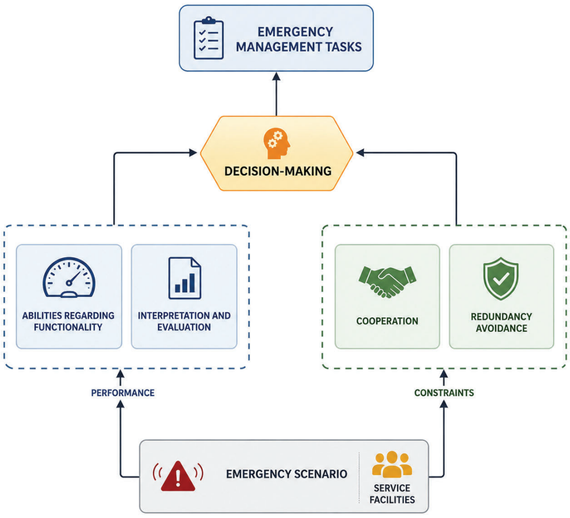

Fig. 9. Optimization-Driven Decision Support Architecture [9]

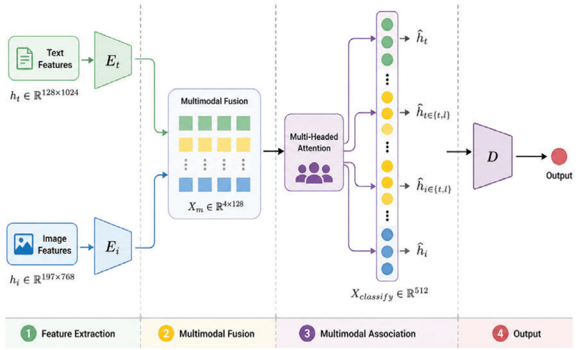

Fig. 10. Multimodal Fusion Framework for Disaster Assessment from Social Media Data [10]

on images often fail to capture the full context of disaster events.

R. Shetty et al. [10] proposed a multimodal deep learning framework that jointly analyzes textual and visual content from social media for disaster assessment. The proposed architecture consists of two parallel branches: a text processing branch and an image processing branch. A fusion module integrates the two modalities into a joint representation that is fed into a classifier for disaster type or severity prediction. Large-scale social media datasets containing paired text and images are used, and the model is trained end-to-end and evaluated against unimodal baselines using standard classification metrics. The multimodal model consistently outperforms text-only and image-only approaches, demonstrating improved robustness and accuracy. The approach depends on the availability of paired text-image data and has higher computational complexity than unimodal systems.

TABLE I
COMPARATIVE SUMMARY OF AI-DRIVEN DISASTER RESPONSE RESEARCH WORKS

Paper	Data Source	Core Technique	Key Contribution
[1]	Social Media	Multimodal Fusion	Improved disaster classification
[2]	Social Media	Open-World Learning	Detection of unseen disasters
[3]	UAV Imagery	Incremental SfM	Near real-time 3D reconstruction
[4]	UAV Imagery	Precision Photogrammetry	GPS-denied modeling
[5]	UAV Imagery	Deep Learning	Real-time damage assessment
[6]	UAV Imagery	Multispectral Fusion	Landslide monitoring
[7]	Aerial / UAV	Change Detection	Near real-time flood change analysis
[8]	UAV Imagery	High-Res Photogrammetry	Bridge deformation monitoring
[9]	System Data	Genetic Algorithms	Optimized decision support
[10]	Social Media	Multimodal Deep Learning	Robust disaster assessment

IV. COMPARISON STUDY

Several studies have proposed AI-driven and photogrammetry-enhanced approaches for disaster response and assessment. These approaches differ in terms of data sources, system architecture, core methodology, and target disaster scenarios. Some systems emphasize real-time multimodal fusion from social media, while others focus on high-precision 3D reconstruction or automated damage quantification from UAV imagery.

Despite their contributions, existing solutions face challenges such as scalability limitations, sensitivity to environmental conditions, lack of real-world deployment evaluation, and limited integration across system components. To highlight these differences and identify research gaps, a comparative analysis of the reviewed works is presented in Table I.

V. SURVEY METHODOLOGY

This survey adopts a systematic methodology to analyze and compare AI-driven disaster response and assessment systems enhanced by photogrammetry. The methodology is designed to ensure comprehensive coverage, objective evaluation, and meaningful comparison of prior research works.

A. *Literature Collection and Selection*

Relevant research articles were collected from reputed digital libraries including IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier ScienceDirect, and Google Scholar. Keywords such as AI-based disaster response, UAV photogrammetry, multimodal disaster classification, 3D reconstruction for disaster assessment, and deep learning damage detection were used during the search process. Only peer-reviewed journal articles, conference papers, and survey studies published in recent years were considered to ensure quality and relevance.

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B. Screening and Classification

The collected studies were screened based on predefined inclusion criteria. Papers focusing on disaster response, damage assessment, photogrammetric reconstruction, social media disaster analysis, or decision support optimization were shortlisted. Only papers directly relevant to the project domain were selected. The selected studies were then classified thematically according to their primary contribution: multimodal information extraction, UAV-based photogrammetry, AI-based damage assessment, change detection, or decision support.

C. Analytical Framework

Each selected work was analyzed using a common analytical framework. Key aspects examined include problem addressed, data sources, system architecture, methodology, performance metrics, results and contributions, and limitations. Special attention was given to performance-related parameters such as inference speed, reconstruction accuracy, scalability, and dataset characteristics. This structured analysis facilitates direct comparison across works and supports identification of recurring patterns and gaps.

D. Comparative Analysis

A comparative study was conducted to identify similarities and differences among existing approaches. The comparison focused on data sources, core techniques, key contributions, and limitations of each system. This analysis helped in identifying recurring challenges such as real-time processing constraints, limited dataset availability, scalability limitations, and integration complexity. The comparison results are summarized in tabular form to enhance clarity and facilitate direct assessment across works.

E. Gap Identification and Synthesis

Based on the comparative analysis, research gaps and open challenges were identified. The synthesis of findings highlights the lack of large-scale real-world deployments, limited open-world generalization, limited integration across heterogeneous system components, and the need for human-centered and uncertainty-aware disaster response solutions. These observations form the basis for the future research directions discussed in this paper.

VI. System Architecture

An integrated AI-driven disaster response system enhanced by photogrammetry encompasses multiple components that collectively enable end-to-end situational awareness from data acquisition to decision support. The overall system architecture comprises the following major modules: multimodal data ingestion, AI-based analysis, photogrammetric reconstruction, damage assessment, and decision support.

The data ingestion layer collects heterogeneous inputs from social media platforms and UAV aerial imagery. Social media data streams are processed by multimodal AI models to extract disaster type, severity, and affected area information. Concurrently, UAV imagery is fed into photogrammetric pipelines to generate dense point clouds and 3D surface models of disaster-affected regions.

The AI analysis layer integrates deep learning models for damage classification and change detection. These models analyze both aerial imagery and reconstructed 3D models to identify and quantify structural damage, terrain deformation, and environmental changes. The photogrammetric reconstruction layer employs SfM and MVS algorithms to generate geometrically accurate 3D models that provide spatial context for rescue operations and resource planning.

The decision support layer synthesizes outputs from the AI and photogrammetry layers, applying optimization algorithms to generate coordinated and prioritized response strategies. A visualization interface presents spatial and semantic information to emergency responders in an interpretable format, supporting effective real-time decision-making.

VII. System Model and Workflow

A typical AI-driven disaster response system enhanced by photogrammetry involves multiple stakeholders including affected communities, UAV operators, AI processing systems, emergency responders, and decision-making authorities.

The workflow begins with data acquisition, where social media monitoring systems collect real-time posts from disaster-affected areas while UAV platforms are deployed to capture high-resolution aerial imagery. Social media data is processed by multimodal AI models for rapid disaster classification and situational awareness, while UAV imagery undergoes photogrammetric processing to generate 3D surface models.

AI-based damage assessment models then analyze the reconstructed 3D models and aerial imagery to identify damaged structures, classify severity levels, and detect changes compared to pre-disaster baselines. These outputs are aggregated and fed into decision support systems, which apply optimization algorithms to prioritize rescue operations, allocate resources, and coordinate multi-agency response activities.

Emergency responders access the processed outputs through visualization interfaces that present spatial maps, damage severity overlays, and recommended response actions. This end-to-end workflow ensures that timely, accurate, and spatially grounded information reaches decision-makers, enabling effective and efficient disaster response.

VIII. Implementation

The implementation of AI-driven disaster response systems enhanced by photogrammetry involves the integration of deep learning frameworks, photogrammetric processing pipelines, and decision support components to enable end-to-end disaster assessment.

A typical implementation begins with configuring data ingestion pipelines for social media monitoring and UAV imagery acquisition. Deep learning models for disaster classification, damage detection, and change analysis are trained on annotated disaster datasets using frameworks such as TensorFlow or PyTorch. Transfer learning is widely employed to adapt pre-trained models to domain-specific disaster datasets.

Photogrammetric reconstruction is implemented using SfM-MVS pipelines. Incremental reconstruction approaches are adopted for near real-time processing, with sliding-window bundle adjustment used to balance accuracy and computational efficiency. Dense point cloud generation and mesh reconstruction are performed to produce spatial models suitable for damage quantification.

Decision support components are implemented using optimization frameworks incorporating metaheuristic algorithms such as genetic algorithms. These components interface with AI and photogrammetric outputs to generate coordinated response strategies that optimize resource allocation and minimize response latency. Integration across components is achieved through modular APIs and standardized data formats. Visualization interfaces are built using GIS platforms or web-based mapping tools, enabling emergency responders to interact with assessment outputs in real time.

A. Implementation Challenges

Implementing AI-driven disaster response systems involves several practical challenges. Real-time processing of large volumes of social media data and UAV imagery requires significant computational resources, often necessitating GPU acceleration and cloud-based infrastructure. Photogrammetric reconstruction, particularly for large geographic areas, remains computationally intensive and introduces latency that can impact response timeliness.

Data availability poses another significant challenge. Annotated disaster datasets are often limited, imbalanced, and domain-specific, restricting the generalizability of trained models. Open-world scenarios, where new or unseen disaster types emerge, further complicate model deployment. Interoperability between heterogeneous system components and integration with existing emergency management infrastructure present additional engineering challenges. Real-world deployment must also address regulatory requirements for UAV operations, data privacy considerations related to social media monitoring, and reliability constraints in communication-degraded disaster environments.

Addressing these challenges requires robust software architectures, adaptive learning strategies, and close collaboration between technology developers and emergency management practitioners.

IX. Research Gaps and Open Challenges

Despite the substantial progress achieved in AI-driven disaster response and assessment systems enhanced by photogrammetry, several research gaps and open challenges remain. Addressing these issues is essential for transitioning existing solutions from research prototypes to large-scale, real-world deployments.

A. Data Availability and Quality

One of the most critical challenges in disaster response research is the limited availability of high-quality, labeled datasets. Disaster events are inherently rare, unpredictable, and diverse, making it difficult to collect balanced datasets that cover all disaster types and severity levels. Social media data is often noisy, incomplete, or misleading, while UAV imagery may suffer from occlusions, motion blur, and inconsistent lighting conditions. Furthermore, most existing datasets are curated post-event and do not fully capture the temporal dynamics of disasters, limiting the ability of AI models to generalize to real-time and evolving disaster scenarios.

B. Scalability and Real-Time Constraints

Many AI and photogrammetry-based systems demonstrate strong performance in controlled experimental settings but struggle to scale to large geographic areas or dense urban environments. Photogrammetric 3D reconstruction, in particular, remains computationally intensive, making near real-time processing challenging for large-scale disasters. Although incremental and near real-time reconstruction techniques have been proposed, there is a trade-off between reconstruction accuracy and processing speed. Designing scalable architectures that balance these competing objectives remains an open problem.

C. Integration of Heterogeneous System Components

Integrated disaster response platforms combine multiple complex components, including multimodal AI models, photogrammetric pipelines, optimization algorithms, and decision support interfaces. Ensuring seamless integration, data synchronization, and fault tolerance across these components is a non-trivial engineering challenge. Most existing studies focus on individual components in isolation, highlighting the need for holistic system-level evaluations that consider end-to-end performance and reliability.

D. Open-World and Uncertainty-Aware Disaster Understanding

Real-world disasters often involve unseen or evolving scenarios that are not represented in training data. While open-world disaster classification approaches have been proposed, robust handling of uncertainty and novelty remains an open research challenge. Future systems must be capable of recognizing unknown disaster patterns, quantifying prediction uncertainty, and adapting to new scenarios without extensive retraining.

E. Human-Centered Design and Trust

The effectiveness of AI-driven disaster response systems ultimately depends on their adoption by emergency responders and decision-makers. Lack of interpretability, explainability, and user trust can hinder practical deployment. There is a growing need for explainable AI techniques, intuitive visualization tools, and human-in-the-loop systems that support collaboration between AI models and domain experts.

X. Future Research Directions

Based on the analysis of existing literature, several promising research directions can be identified for advancing AI-driven disaster response and assessment systems.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

A. Cloud-Native and Edge-AI Architectures

Future systems should explore cloud-native and edge-AI architectures to improve scalability and reduce latency. Distributed processing, GPU acceleration, and edge computing can enable real-time analysis of multimodal data streams and photogrammetric reconstruction at scale.

B. Continual and Self-Supervised Learning

Continual learning and self-supervised learning approaches can reduce dependency on labeled data and enable models to adapt to new disaster scenarios over time. These techniques are particularly relevant for open-world disaster response applications.

C. Advanced Multimodal and Multispectral Fusion

Deeper integration of multimodal and multispectral data, including thermal imagery, satellite data, and IoT sensor streams, can enhance situational awareness and damage assessment accuracy. Future research should focus on robust fusion strategies that handle missing or unreliable modalities.

D. Large-Scale Field Deployment and Validation

There is a pressing need for large-scale field deployments and real-world validation studies involving emergency agencies, government bodies, and NGOs. Such studies are essential for evaluating system robustness, usability, and societal impact under real disaster conditions.

XI. Conclusion

This survey presented a comprehensive and in-depth review of AI-driven disaster response and assessment systems enhanced by photogrammetry. The study systematically analyzed research works focusing on multimodal disaster information extraction from social media, UAV-based photogrammetric 3D reconstruction, AI-based damage assessment, multispectral change detection, and optimization-driven decision support systems.

The survey highlighted that integrated AI–photogrammetry frameworks offer significant advantages over unimodal or isolated approaches by combining semantic understanding with accurate spatial awareness. Such systems enable faster situational assessment, improved decision-making, and more efficient coordination of disaster response activities.

Despite these advancements, challenges related to scalability, real-time performance, open-world generalization, and human-centered design remain open. Addressing these challenges will be critical for realizing the full potential of AI-driven disaster response systems in real-world deployments. Overall, this survey provides a structured foundation for future research and development in AI-driven disaster response and assessment, with a strong emphasis on integrated, scalable, and human-centered solutions.

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