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DEEP LEARNING TECHNIQUES FOR QUADCOPTER-BASED UAV SYSTEMS: APPLICATIONS AND CHALLENGES

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Abstract: *Unmanned aerial vehicles (UAVs), particularly quadcopters, integrated with deep learning techniques have transformed aerial monitoring across diverse domains, including security surveillance, target tracking, traffic monitoring, precision agriculture, and disaster management. This review examines the evolution of object detection methods from traditional handcrafted feature-based approaches to modern deep learning frameworks, highlighting the development and application of one-stage and two-stage detectors in UAV imagery. Key challenges associated with deploying deep learning on UAV platforms, including limited onboard computational resources, energy constraints, communication latency, complex backgrounds, small-object detection, class imbalance, and arbitrary object orientations, are critically discussed. The review further explores recent applications of UAV-based deep learning systems in traffic surveillance, crop health assessment, flood and wildfire monitoring, and post-disaster damage evaluation. In addition, operational considerations such as obstacle avoidance, battery management, adverse weather conditions, flight control, noise suppression, and communication range are examined. Overall, the reviewed literature demonstrates that the combination of quadcopters and deep learning provides accurate, scalable, and cost-effective solutions for intelligent aerial monitoring. Future advances in lightweight models, edge computing, multisensor fusion, and autonomous decision-making are expected to further enhance the performance, reliability, and real-world deployment of UAV-based monitoring systems.*

Key words: *UAV; Quadcopter; Deep learning; Algorithm; Object Detection.*

1 Introduction

1.1 Unmanned Aerial Vehicle (UAV)

In recent years, unmanned aerial vehicles (UAVs) have experienced substantial growth in both research and practical deployment. UAVs have emerged as promising platforms for a wide range of applications, including firefighting, mapping, reconnaissance, disaster response, and search-and-rescue operations. Additional civilian applications include inspection and surveillance, aerial photography, precision agriculture, traffic and crowd monitoring, meteorological observation, emergency healthcare delivery, and parcel transportation. These capabilities are enabled by advances in UAV design, allowing autonomous navigation, beyond-visual-line-of-sight operation, and robust performance in challenging terrains and adverse weather conditions. UAVs may be remotely operated using radio controllers, classified as remotely piloted aircraft (RPA), or operate with varying levels of autonomy ranging from assisted flight to fully autonomous systems using GPS-enabled navigation. The selection of onboard cameras, sensors, and control systems depends on the intended application. The main UAV platforms include fixed-wing, helicopter, and multirotor systems (Rendón and Martins, 2017; Janarthanan *et al*., 2019; Qays *et al*., 2020; Dilshad *et al*., 2020; Shahi *et al*., 2022; Debas *et al*., 2024). Drones offer significant advantages over traditional platforms such as manned aerial vehicles and satellites. These include low-altitude operation, high-resolution imaging, and cost-effective environmental monitoring. Advances in drone technology have enhanced their operational capabilities, making them essential tools in real-time surveillance and infrastructure inspection applications. Consequently, their adoption continues to grow across both academic and industrial domains. Drones can operate indoors and outdoors at varying speeds, using onboard sensors for obstacle detection and navigation. Their versatility makes them suitable for replacing human involvement in hazardous, complex, or physically demanding tasks (Akbari *et al*., 2021). Originally developed for military purposes, drones were referred to by various names such as Unmanned Aerial Vehicles (UAVs), miniature pilotless aircraft, and flying mini robots. Their applications have since expanded into sectors such as agriculture, construction, mining, insurance, telecommunications, entertainment, security, and transportation. The expanding market potential of drones as shown in Table 1 highlights their growing industrial relevance (Hafeez *et al*., 2023).

Table 1: Drone use across sectors (Hafeez *et al*., 2023)

S.No.	Industry	Drone application	Budget (Source: PwC (2016))
1	Infrastructure	Investment monitoring, Maintenance, Asset inventory	$45.2 bn
2	Agriculture	Analysis of soils and drainage, Crop health monitoring, Yield prediction, Pesticides and fertilizer spot spraying	$32.4 bn
3	Transport	Delivery of goods, Medical Logistic	$13.0 bn
4	Security	Monitoring lines and sites, Proactive response	$10.5 bn
5	Entertainment and Media	Advertising, Entertainment, Aerial Photography, Shows and Special Effect	$8.8 bn
6	Insurance	Support in claims settlement process, Fraud detection	$6.8 bn
7	Telecommunication	Tower maintenance, Signal broadcasting	$6.3 bn
8	Mining	Planning, Exploration, Environmental impact assessment	$4.3 bn

Among UAV platforms, quadcopters are the most widely adopted due to their agility, hovering capability, and ease of control. Quadcopters are rotorcraft UAVs consisting of four propellers mounted on a rigid frame in either a "+" or "×" configuration, enabling precise control of thrust and orientation. Compared to conventional aircraft, their compact structure results in lower manufacturing cost, reduced power consumption, and suitability for indoor operations. The geometric symmetry of quadcopters simplifies modelling and controller design, while their vertical take-off and landing (VTOL) capability provides operational flexibility in constrained environments. These advantages make quadcopters suitable for surveillance tasks in locations where traditional security infrastructure is limited or unavailable (Pashaei *et al*., 2020; Iqbal *et al*., 2021; Karam *et al.,* 2024). Figure 1 shows the applications of quadcopter.

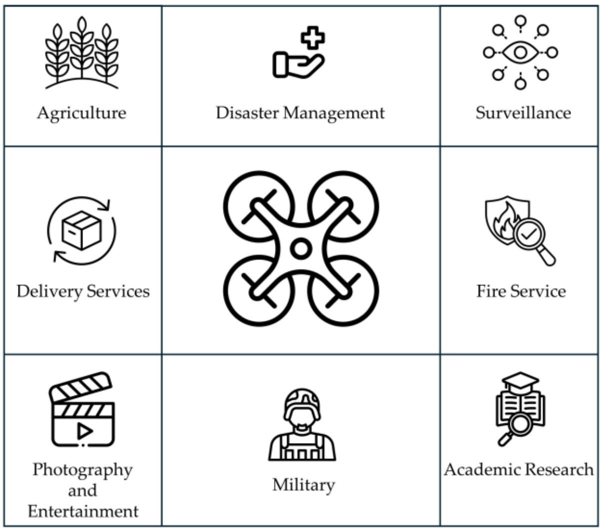

Figure1: Quadcopter Applications (Karam *et al.*, 2024)

Recent developments in artificial intelligence (AI)-driven control systems have significantly enhanced UAV autonomy. Advances in deep learning generalization have enabled improved decision-making and automation. Deep learning forms the foundation of many AI systems, enabling analytical and physical task execution without human intervention. AI systems can perform autonomous decision-making and real-time data analysis based on prior training experiences (Heidari, 2022; Chen *et al.*, 2023; Hafeez *et al*., 2023). The broader field of AI has evolved rapidly with the emergence of machine learning and deep learning, which are capable of processing large-scale data, generating predictions, and extracting complex patterns (Koosha and Amini, 2018). In general, AI refers to computational systems that replicate human intelligence by performing reasoning, learning, perception, and decision-making tasks using techniques such as rule-based systems, fuzzy logic, genetic algorithms, and multi-agent systems (Janiesch *et al*., 2021).

Given the rapid advancement of deep learning and its increasing integration with quadcopter platforms, it is timely to provide a comprehensive review of current developments in this field. The objective of this paper is to examine recent advances in deep learning-enabled quadcopter systems and their applications across security surveillance, target tracking, traffic monitoring, precision agriculture, and disaster management. In addition, this review analyses the key technical and operational challenges associated with deploying deep learning models on quadcopters, including computational limitations, energy constraints, communication requirements, and environmental factors. Furthermore, the paper identifies current research gaps and emerging trends, highlighting future directions for the development of more robust, efficient, and intelligent UAV systems. The main contribution of this review lies in synthesizing recent literature, critically discussing existing approaches, and providing a consolidated perspective on the opportunities and challenges of integrating deep learning with quadcopter platforms.

1.2 Machine Learning

Machine learning is a technology for developing computer algorithms that emulate human intelligence. Machine learning (ML), one of the commonly used AI approaches, describes the intelligence demonstrated by computers. If artificial intelligence is viewed as a brain, then machine learning represents the process through which AI acquires new cognitive abilities, while deep learning represents the most advanced self-training system currently available. ML is a method of data analysis that automates model building, enabling systems to learn and improve from experience in performing tasks using input data without being explicitly programmed. Instead of being hard-coded, ML systems improve through experience by adjusting their internal structure during a process known as training. During training, algorithms use sample data and desired outputs to optimize performance and generalize to new, unseen data. Like humans, effective algorithms can continue learning over time, refining their accuracy as more information is processed (El Naqa *et al*., 2015; Koosha and Mahyar, 2018; Heidari, 2022; Mohammad Mustafa, 2023).

Machine learning (ML), a subset of AI, focuses on developing algorithms that learn patterns from data and improve performance over time without explicit programming. ML models are trained using datasets to optimize prediction accuracy and are widely applied in domains such as object recognition, speech processing, natural language processing, cybersecurity, and autonomous systems. Learning occurs through a training phase, where models are exposed to data, and a testing phase, where performance is evaluated on unseen inputs (Jordan and Mitchell, 2015; Baig *et al*., 2022).

1.3 Deep Learning

Deep learning (DL), a subset of machine learning, employs neural networks that mimic the structure and function of the human brain (Mohammad Mustafa, 2023). These models are particularly effective for processing unstructured data and solving complex problems such as image and speech recognition. Deep learning architectures use multilayer neural networks to learn hierarchical feature representations (Koosha and Mahyar, 2018). This branch of machine learning (ML) uses multilayer neural network architectures that capture increasingly complex data patterns. Evolving from single-layer neural networks (Swart and Mienye, 2024). Common architectures include feedforward networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs), among others (Mohammed and Kora, 2023). CNNs have achieved significant success in image-based applications such as object detection and classification. Since deep learning (DL) is built upon neural network structures, its models are referred to as deep neural networks (Mohammad Mustafa, 2023).

In UAV-based applications, computer vision plays a critical role in translating 2D image data into meaningful 3D environmental information. This process involves image acquisition, processing, analysis, and interpretation. Computer vision enables automated extraction of spatial and semantic information such as object identity, position, and orientation (Koosha and Mahyar, 2018; Akbari *et al*., 2021; N. Sun *et al*., 2022). Deep learning, particularly CNN-based architectures, is widely used in computer vision applications for UAV systems (Heidari, 2022). Advanced models such as transformer networks, RNNs, and generative adversarial networks (GANs) further enhance visual perception capabilities (Mohammad Mustafa, 2023).

1.4 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are among the most widely used deep learning architectures for image recognition. CNNs perform feature extraction through convolutional layers, feature selection through pooling layers, and classification through fully connected layers, as illustrated in Figure 2. These operations enable effective learning of spatial hierarchies in image data. CNNs have been successfully applied in object recognition and image classification tasks (Koosha and Mahyar, 2018; Heidari, 2022). Originally developed for image processing, CNNs use convolutional layers to capture spatial hierarchies within data, achieving remarkable success in tasks such as image and video recognition (Mienye and Swart, 2024).

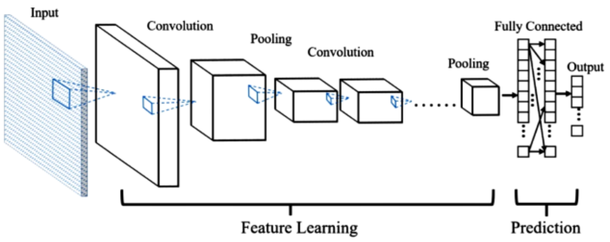

Figure 2: CNN Architecture (Mienye and Swart, 2024)

Object detection extends image classification by identifying and localizing multiple objects within an image using bounding boxes. Modern object detection models are trained on large, labelled datasets and evaluated using metrics such as precision. Due to the success of CNNs, object detection has become widely adopted and is typically categorized into single-stage and two-stage methods (Zhao et al., 2018; Khan et al., 2019; Lin et al., 2021; Zaidi et al., 2022). In UAV surveillance systems, object detection is critical for real-time applications such as tracking, search, and rescue, where high accuracy and low latency are required (Lin et al., 2021; Zaidi et al., 2022).

Recent advances in deep learning have significantly improved the autonomy and intelligence of quadcopter-based surveillance systems. CNNs, RNNs, and transformer models enhance perception tasks such as object detection, recognition, and tracking from aerial imagery. State-of-the-art models such as YOLO, Faster R-CNN, and SSD enable real-time object localization under dynamic conditions. In addition, reinforcement learning improves adaptive flight control, obstacle avoidance, and target tracking, enabling more intelligent UAV behaviour in complex environments. Hence, it is timely to provide a detailed survey that assimilates and categorizes the performance of deep learning methods in quadcopter systems (Shahi et al., 2022). This paper reviews studies on quadcopter-captured image and video datasets and their application in surveillance tasks. It highlights the use of deep learning techniques for target tracking, traffic monitoring, accident detection, disaster management, and agricultural analysis. Furthermore, it discusses key challenges in deep learning-based UAV deployment, system design considerations, and the underlying principles of quadcopter technology.

1.5 Taxonomy of Deep Learning Models Used in Quadcopter Applications

The taxonomy of deep learning is shown in Table 2.

Table 2: Taxonomy of Deep Learning Models Commonly Used in Quadcopter-Based Applications

Model Category	Representative Models	Typical Quadcopter Applications
CNN-based Classification	ResNet, VGG, MobileNet	Crop disease detection, damage assessment, surveillance
One-Stage Object Detection	YOLOv3, YOLOv5, YOLOv8, SSD	Real-time surveillance, traffic monitoring, target detection
Two-Stage Object Detection	Faster R-CNN, Mask R-CNN	High-accuracy surveillance and structural damage assessment
Semantic Segmentation	U-Net, DeepLabV3+, FCN	Flood mapping, wildfire monitoring, landslide detection
Tracking Models	DeepSORT, Siamese Networks	Target tracking and vehicle tracking
Transformer-Based Models	DETR, Vision Transformer (ViT)	Complex scene analysis and disaster monitoring
Reinforcement Learning Models	DQN, MADDPG	Autonomous navigation and multi-UAV coordination

2 Review Methodology

This review was conducted through a comprehensive survey of published literature on the integration of deep learning techniques with quadcopter-based UAV systems. Relevant articles were retrieved from major scientific databases, including Google Scholar, IEEE Xplore, ScienceDirect, SpringerLink, Scopus, and Web of Science. The literature search focused on publications between 2019 and 2025 to capture recent advances in UAV-based deep learning applications.

Keywords used during the search included “quadcopter UAV”, “deep learning”, “object detection”, “target tracking”, “security surveillance”, “precision agriculture”, “traffic monitoring”, “flood monitoring”, “wildfire detection”, “earthquake damage assessment”, “landslide monitoring”, and “edge computing UAV”.

Articles were selected based on their relevance to deep learning applications in quadcopter systems. Preference was given to peer-reviewed journal articles, conference papers, and review articles that presented significant methodological contributions, experimental evaluations, or practical implementations. Studies unrelated to quadcopter platforms, lacking sufficient technical detail, or presenting duplicate findings were excluded.

The selected literature was analyzed and organized into thematic categories, including surveillance, tracking, agriculture, disaster monitoring, and system integration challenges. A comparative synthesis of the findings was then conducted to identify current trends, achievements, limitations, and future research directions in deep learning-enabled quadcopter systems.

2.1 Fundamental Concept

This section introduces the essential principles behind quadcopters and the importance of computer vision for use in UAVs.

2.1.1 Quadcopter System

A quadcopter is a multirotor UAV propelled and lifted by four motors. These motors control the drone's motion by adjusting their rotational speeds, thereby varying thrust and torque. Quadcopters have six degrees of freedom but only four actuators, making them underactuated systems that require stabilizing controllers for stable flight. To prevent continuous rotation, the propellers are configured such that two rotate clockwise and the other two anticlockwise, ensuring torque balance. For independent control of motion, specific motor arrangements are used, where pairs of motors rotate in opposite directions to maintain equilibrium and enable manoeuvrability. Quadcopters are typically equipped with an Inertial Measurement Unit (IMU), consisting of accelerometers, gyroscopes, and sometimes magnetometers, to estimate and control orientation. Additional sensors such as GPS, barometers, and proximity sensors may also be integrated to enhance navigation in both indoor and outdoor environments. Quadcopters are commonly designed in two configurations, the "+" and "X" formations, which define the orientation of the frame relative to the direction of flight (Altinors and Kuzu, 2021; Allende Peña et al., 2021; Kangunde et al., 2021; Ye et al., 2021).

2.1.2 Quadcopter Control System

Quadcopter control consists of four fundamental control inputs that govern its motion and behavior. The first is yaw, which refers to rotation about the vertical z-axis. It is achieved by varying the relative speeds of clockwise and counterclockwise propellers, generating a net torque that causes rotation around the vertical axis. The second is roll, which describes angular motion about the x-axis and is controlled by adjusting the speed difference between the left and right propellers, producing a torque that tilts the quadcopter laterally. The third is pitch, representing angular motion about the y-axis, and is achieved by varying the speeds of the front and rear propellers to induce forward or backward tilting. The fourth is throttle, which controls the overall lift by uniformly increasing or decreasing the rotational speed of all four propellers; when balance is maintained, throttle primarily determines altitude (Teppo Luukkonen, 2011; Dams, 2014; Liu, 2024).

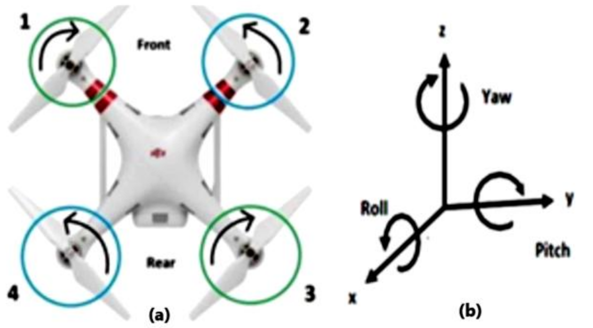

Figure 3: a) Quadcopter with four rotors

b) Roll, pitch and yaw angles that define the motion of the quadcopter (Altinors and Kuzu, 2021).

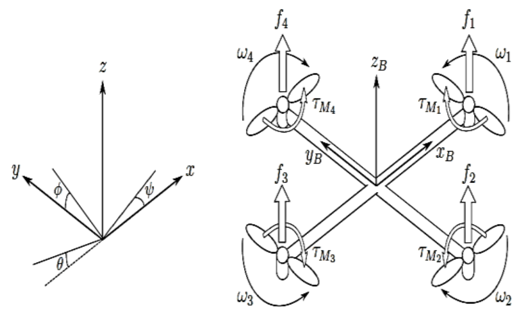

Figure 4: Force Analysis of a Quadrotor (Teppo Luukkonen, 2011)

The quadcopter, including its rotors and rotation angles, is illustrated in Figure 3, while the force analysis is presented in Figure 4. UAVs operate independently of ground-based infrastructure, enabling access to remote or hard-to-reach environments for various applications. Many companies have developed specialized drone platforms to reduce operational and labour costs. During design and production, key factors such as aircraft weight, energy consumption, and thermal management are critical considerations. To perceive their environment and estimate position and orientation, UAVs are equipped with a range of sensors, including exteroceptive and proprioceptive systems such as GPS. Additional sensors, including ultrasonic sensors and visual cameras (stereo or monocular), are used for obstacle detection, avoidance, and 3D environment mapping. These systems can be further integrated with laser range finders and inertial measurement units (IMUs) to improve accuracy and enable precise visual–inertial motion estimation (Akbari et al., 2021; Balestrieri et al., 2021; Thalagala et al., 2024).

2.1.3 Object Detection

Object detection using quadcopters involves the identification, localization, and classification of objects from aerial images or video streams captured by onboard sensors. Although different deep learning models such as YOLO, Faster R-CNN, SSD, and ResNet-based architectures are employed across studies, the general object detection workflow remains largely consistent (Kaya et al., 2021; Salido et al., 2021; Kambhatla and Khaled, 2023)

Step 1: Data Acquisition

Quadcopters capture aerial imagery using onboard RGB, infrared, or multispectral cameras, depending on the application requirements. Video streams are often decomposed into individual frames for subsequent analysis.

Step2: Preprocessing

The acquired images undergo pre-processing operations such as resizing, normalization, colour correction, noise reduction, and data augmentation techniques including rotation, flipping, and scaling. These operations improve model robustness under varying lighting conditions, altitudes, and viewing angles (Salido et al., 2021).

Step 3: Object Detection with Deep Learning

Deep learning models are employed to identify objects within each frame and generate bounding boxes, class labels, and confidence scores. Popular object detection approaches include YOLO (You Only Look Once), which is widely recognized for its real-time detection capability and computational efficiency; Faster R-CNN, which generally provides higher detection accuracy, particularly for small or partially occluded objects, albeit at a greater computational cost; and Single Shot MultiBox Detector (SSD), which offers a balance between detection speed and accuracy. Other notable object detection architectures include RetinaNet, which addresses class imbalance through focal loss; EfficientDet, which achieves high accuracy with optimized computational efficiency; and DETR (Detection Transformer), which leverages transformer-based architectures for end-to-end object detection. In addition, ResNet-based architectures, such as ResNet-50 and ResNet-FPN, are frequently employed as backbone networks for feature extraction in object classification and localization tasks.

Step 4: Post-Processing

Post-processing techniques such as Non-Maximum Suppression (NMS) are applied to eliminate redundant or overlapping bounding boxes. In video-based applications, object tracking algorithms may further associate detections across consecutive frames to support continuous monitoring.

Step 5: Visualization and Decision Making

The final output consists of annotated images or video streams containing localized objects and corresponding class labels. These outputs can be used for surveillance, traffic monitoring, disaster assessment, search and rescue operations, and other aerial monitoring applications.

2.1.4 Evolution of Object Detection Algorithms

The evolution of object detection algorithms can be broadly categorized into two main stages: traditional methods and deep learning–based approaches. Deep learning–based methods are further divided into one-stage and two-stage detection frameworks. As illustrated in Figure 5, object detection has undergone significant development from early approaches in the 2000s to modern deep learning architectures between 2012 and 2023. Traditional object detection methods primarily relied on sliding-window techniques and handcrafted feature extraction. These approaches typically follow a three-stage pipeline: region proposal, feature extraction, and classification/regression. In the region proposal stage, candidate image regions likely to contain objects are identified. These regions are then converted into feature representations using manually designed descriptors, after which classifiers are applied to determine object categories. Although foundational, these methods are computationally expensive and limited in their ability to represent complex visual features. Notable examples include the Viola–Jones detector and Histogram of Oriented Gradients (HOG)-based pedestrian detection frameworks (Diwakar and Raj, 2022; Tang et al., 2024).

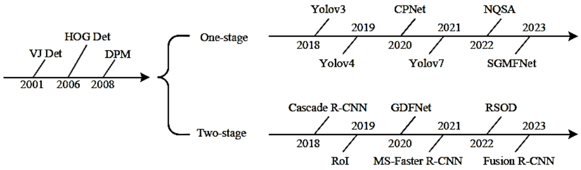

Figure 5: object detection evolution (Tang *et al.*, 2024)

The introduction of convolutional neural networks (CNNs) marked a breakthrough in object detection research. CNN-based methods enabled automatic feature learning directly from raw images, significantly improving detection accuracy and robustness. Early deep learning approaches introduced region-based frameworks that improved performance over traditional methods but introduced computational complexity due to multiple processing stages. Two-stage detectors operate by first generating region proposals and then classifying these regions in a second stage. While highly accurate, these methods often incur higher computational costs and are less suitable for real-time applications. As illustrated in Figure 6, this framework addresses challenges such as precise localization, boundary refinement, and multi-scale object detection. Representative two-stage detectors include R-CNN, Spatial Pyramid Pooling Network (SPPNet), Fast R-CNN, Faster R-CNN, Mask R-CNN, and Feature Pyramid Networks (FPN) (Lu et al., 2020; Olorunshola et al., 2023; Tang et al., 2024).

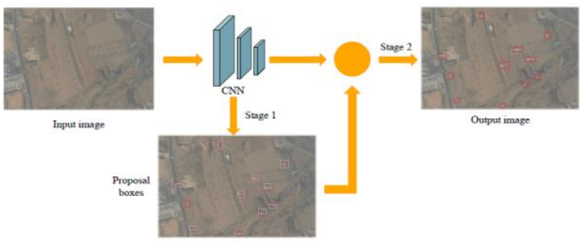

Figure 6: Two-Staged Object Detector (Tang *et al.*, 2024)

In contrast, one-stage detectors eliminate the region proposal stage and perform direct object classification and localization in a single pass, significantly improving computational efficiency. However, these methods may suffer from reduced accuracy in detecting small or densely packed objects due to class imbalance and limited feature refinement. As illustrated in Figure 7, one-stage detectors are widely used in real-time applications where speed is critical. Representative models include the YOLO family (YOLOv1–YOLOv26), Single Shot MultiBox Detector (SSD), RetinaNet, EfficientDet, and anchor-free detectors such as FCOS and CenterNet (Tang et al., 2024; Carranza-García et al., 2021). Recent advances have further expanded object detection through transformer-based architectures such as DETR (Detection Transformer) and its variants, which formulate object detection as a set prediction problem and eliminate the need for handcrafted anchors and post-processing in traditional pipelines.

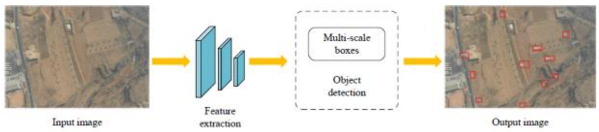

Figure 7: One-Stage Detector (Tang *et al.*, 2024)

While the general framework of object detection using quadcopters provides a conceptual foundation, practical implementations vary depending on the application domain and selected deep learning architecture. The subsequent sections review studies that integrate UAV platforms with deep learning–based object detection for applications such as surveillance, traffic monitoring, and disaster response.

3 Quadcopters and Deep Learning Applications

With advancements in UAV technology, drones equipped with cameras and onboard computing systems are increasingly applied across diverse domains such as agriculture, power-line inspection, aerial photography, mapping, surveillance, and infrastructure monitoring. These applications require UAVs to perceive their environments, interpret visual scenes, and respond effectively, making automated object detection a core enabling capability. Deep learning–based object detection methods, particularly those built on convolutional neural networks (CNNs), automatically learn hierarchical image features, thereby significantly improving detection accuracy and overall system performance (Tang *et al.*, 2024).

This section examines the use of quadcopter-captured images and video data in applications such as surveillance, agriculture, disaster monitoring, traffic analysis, and facial recognition. It further reviews the existing literature on the deployment of quadcopters in these domains and highlights key deep learning approaches for image detection and classification.

3.1 Surveillance

An important application of quadcopters is surveillance, which involves continuous monitoring of environments for information gathering, security enhancement, and situational awareness. Key surveillance tasks include security monitoring, traffic analysis and accident detection, and target tracking.

3.1.1 Security Surveillance

Security surveillance using quadcopters has been shown to be effective when integrated with deep learning techniques. M. J. Iqbal et al., (2021) proposed a cost-effective and efficient surveillance framework that leverages deep learning models for real-time video analysis. The study highlights the limitations of traditional surveillance systems, which are often computationally intensive and expensive, and instead introduces convolutional neural networks (CNNs) for automatic feature extraction and classification in live video streams. Their approach includes a comparative evaluation of pretrained CNN architectures, including SqueezeNet, GoogLeNet, ResNet-50, and ResNet-18. The system is deployed on surveillance feeds to detect suspicious activities and track individuals, with emphasis on balancing model complexity and inference speed to achieve real-time performance. Experimental results demonstrate high accuracy in object detection and activity recognition while maintaining low latency, confirming the effectiveness of deep learning in enhancing surveillance systems.

Hoang (2023) proposed a real-time multi-object tracking framework for UAV surveillance based on a tracking-by-detection approach using deep learning techniques. The system employs a convolutional neural network-based detector to identify multiple targets in aerial video frames, followed by feature extraction and data association mechanisms to maintain object identities across consecutive frames. The tracking module links detected objects over time based on spatial and appearance consistency, enabling robust multi-target tracking under dynamic UAV motion. Experimental results demonstrate improved tracking accuracy, reduced identity switching, and strong performance under occlusion and complex environmental conditions, highlighting the effectiveness of deep learning-based multi-object tracking for UAV surveillance applications.

Xu *et al*. (2024) developed a UAV-based intrusion detection and tracking system using a 360° panoramic camera combined with a 3-axis gimbal and deep learning techniques. The study employs an improved YOLOv5s-based object detection model (YOLOv5s-360ID) for intrusion detection and classification of targets within aerial images. The framework integrates convolutional neural network (CNN)-based feature extraction within the YOLO architecture, while panoramic imaging provides wide-area coverage, and the gimbal ensures stable tracking of moving targets. The system achieved over 90% detection accuracy and demonstrated strong robustness under challenging conditions such as variable lighting and cluttered environments. The study highlights that combining panoramic vision with YOLO-based deep learning significantly improves situational awareness and reduces blind spots in UAV surveillance systems.

Cai et al. (2024) addressed the challenge of UAV interception by developing a framework that integrates flight control strategies with intelligent pursuit and decision-making algorithms. The system enables interceptor UAVs to detect intruding drones, estimate their trajectories, and execute real-time interception manoeuvres using reinforcement learning-based control policies. Specifically, an EA-MADDPG multi-agent reinforcement learning algorithm is employed to model cooperative interception behaviour, where agents learn optimal strategies based on environmental state information. The approach is further combined with path planning and adaptive flight control to ensure stability and accuracy during high-speed operations. Experimental results show improved interception success rates and reduced response times compared to conventional approaches, demonstrating the effectiveness of UAV-to-UAV defensive systems.

Elshaar et al. (2024) evaluated deep learning models for detecting quadrotor UAVs in surveillance scenarios, focusing on the trade-off between accuracy and computational efficiency. The study benchmarked YOLOv5, YOLOv8, and Faster R-CNN using UAV-specific aerial datasets under varying environmental conditions. Results indicate that YOLOv8 achieved the best balance between detection accuracy and inference speed, making it suitable for real-time surveillance applications, while Faster R-CNN achieved higher precision at the cost of increased latency. The findings confirm that one-stage detectors are more practical for real-time UAV surveillance, whereas two-stage detectors remain preferable when maximum accuracy is required.

Okhiria *et al.* (2025) proposed a real-time aerial surveillance system for quadcopter UAVs using machine vision and YOLO-based deep learning models. The system enables autonomous object detection and tracking in dynamic environments using onboard cameras. Experimental results show high detection accuracy and low latency, demonstrating improved performance over traditional handcrafted vision methods. The study highlights the effectiveness of combining UAV mobility with deep learning for applications such as border security, search and rescue, and public safety monitoring.

Abdou and Aziz (2021) presented a UAV surveillance framework that addresses onboard computational limitations by using off-board processing. Video data captured by UAVs is transmitted to ground stations or edge servers for real-time analysis using YOLO-based CNN models. This approach reduces onboard processing load, improves inference speed, and extends UAV operational time. The results show that off-board computation provides a practical trade-off between accuracy, efficiency, and energy consumption in UAV surveillance systems.

Dobrea and Dobrea (2020) developed a quadcopter-based surveillance system for monitoring public health compliance during the COVID-19 pandemic. The system integrates onboard cameras with embedded computing devices such as Raspberry Pi and NVIDIA Jetson Nano for real-time video processing. The study compares classical machine learning methods such as SVM with deep learning CNN-based approaches, demonstrating that CNNs significantly outperform traditional methods in detection accuracy and robustness. The Jetson Nano platform provides improved real-time performance, enabling continuous surveillance in dynamic environments.

J. Kim and Cho (2021) proposed an efficient onboard object detection system for UAV air-to-ground surveillance using Faster R-CNN. The system integrates region proposal networks with CNNs to perform real-time object detection directly on embedded hardware. Experimental results show high detection accuracy and reliable localization performance, although with higher computational cost compared to lightweight one-stage detectors. The study demonstrates that Faster R-CNN remains effective for high-precision surveillance applications where accuracy is prioritized over speed.

Dilshad et al. (2020) conducted a comprehensive survey on UAV-based video surveillance, highlighting applications in object detection, tracking, traffic monitoring, disaster response, and search and rescue. The study identifies key challenges such as camera instability, occlusion, and real-time processing limitations. Proposed solutions include CNN-based pre-processing, resource-efficient tracking models, and integration of high-resolution sensors to improve detection accuracy and robustness in complex environments.

Darwante et al. (2019) proposed a UAV-based border surveillance system using YOLOv3 for real-time object detection and classification. The system enables autonomous patrol and continuous monitoring of border regions, reducing reliance on human patrols. Experimental results demonstrate improved situational awareness, reduced blind spots, and faster response times, highlighting the effectiveness of UAV-based surveillance systems for security-critical applications.

Overall, the reviewed studies show that deep learning has greatly enhanced quadcopter-based security surveillance by improving object detection, tracking, and activity recognition. Recent research has shifted from conventional CNN-based approaches toward lightweight YOLO models, multi-object tracking, and reinforcement learning techniques to achieve real-time performance. While high detection accuracy has been widely reported, challenges related to onboard computational resources, occlusions, and complex operating environments remain. These findings suggest that UAV-based surveillance systems are becoming increasingly intelligent, efficient, and autonomous, with ongoing efforts focused on balancing accuracy and real-time deployment requirements.

3.1.2 Target Tracking

Target tracking using quadcopters extends object detection by continuously identifying and following targets across video frames while compensating for UAV motion. The process typically begins with data acquisition using onboard RGB or thermal cameras, sometimes supported by GPS and inertial sensors for stabilization (Soeleman *et al.*, 2023). Deep learning–based object detectors such as YOLO, Faster R-CNN, and SSD generate bounding boxes and class labels for each frame (Ni *et al.*, 2024; Wang *et al.*, 2023). To maintain temporal consistency, motion models such as Kalman filters are commonly used to predict target positions between frames and mitigate occlusion effects (Wu *et al.*, 2022). Data association methods, including DeepSORT and Hungarian-based matching algorithms, link detections across frames using spatial and appearance features (Du *et al.*, 2023). In active tracking scenarios, these outputs are translated into flight control commands that adjust UAV position and orientation to maintain continuous focus on the target. Depending on system design, tracking models may be deployed on-board for real-time operation or off-board on ground stations to improve computational efficiency and accuracy (Wang *et al.*, 2023). Standard UAV tracking benchmarks such as VisDrone and UAVDT are widely used for evaluation using metrics such as Multiple Object Tracking Accuracy (MOTA) and identity switch counts (Wu *et al.*, 2022). Overall, effective quadcopter-based tracking integrates detection, motion prediction, and data association to achieve robust performance in dynamic aerial environments (Du *et al*., 2023; Ni *et al*., 2024) Figure 8 shows UAV object detection and tracking system.

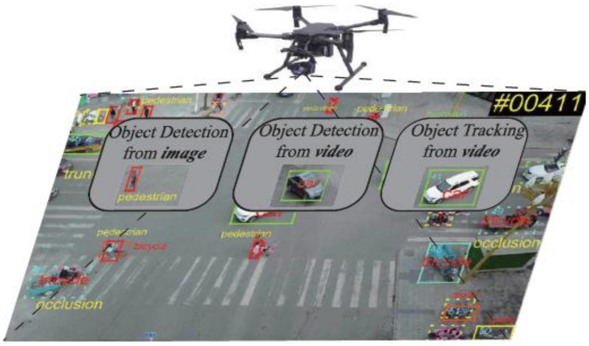

Figure 8: UAV object detection and tracking(Wu *et al.*, 2022)

Beyond conventional CNN-based tracking, recent studies have explored more advanced architectures to address challenges such as occlusion, target loss, and scale variation. N. Sun *et al*. (2022) proposed a transformer-based aerial tracking framework combining spatial and temporal dimensions to solve challenging problems in aerial tracking like target loss, misclassification, and imprecise boundary boxes. The framework entails a feature extraction and correlation network, a temporal update strategy, and a prediction head. They proposed a trans-UAV using a feature correlation network based on a self-attention mechanism. The VTUAV considered detailed application in various scenarios such as long and short-term tracking. Using a recently published VTUAV dataset, experiments were conducted.

Li *et al*. (2020) addressed manoeuvring target tracking in uncertain UAV environments using deep reinforcement learning combined with meta-learning. Their approach enables rapid adaptation to new target behaviours and environmental changes without retraining, improving generalization across diverse tracking tasks.

S. Wu *et al*. (2021) developed a vision-based UAV tracking framework integrating detection, state estimation, and flight control modules. The system enables real-time target pursuit by combining onboard visual perception with predictive trajectory estimation and control feedback.

Hong *et al*. (2023) enhanced multi-target tracking by integrating YOLOv4-based detection with an improved DeepSORT tracking algorithm. The system improves identity preservation and reduces ID switches in crowded aerial environments through refined deep appearance embeddings, demonstrating strong performance in surveillance and traffic monitoring applications.

Visundhara *et al.* (2025) proposed a real-time drone tracking system combining CNN-based detection, YOLO object detection, and Kalman filtering for robust target localization. The system also incorporates sensor fusion using RGB cameras and LiDAR to enhance performance under low-visibility and dynamic conditions.

Elshaar *et al*. (2024) evaluate the performance of deep learning models, specifically YOLOv5 and YOLOv8, for quadrotor UAV detection and tracking, motivated by growing concerns around drone surveillance, privacy, and safety. Their study systematically benchmarks these models across multiple datasets and scenarios, analyzing detection accuracy, tracking stability, and computational efficiency. Results show that YOLOv8 consistently outperforms YOLOv5, particularly in detecting small aerial targets and handling complex backgrounds.

Yu *et al*. (2023) proposed a transformer-based tracking framework for anti-UAV applications, improving long-range dependency modelling and reducing identity switches under complex aerial conditions.

Hanzla *et al*. (2024) improved UAV-based vehicle tracking using an enhanced DeepSORT framework with aerial-specific re-identification training, improving trajectory consistency and reducing tracking errors in UAV-captured imagery. Their work addresses the challenges of small object sizes, occlusion, and viewpoint variation that are common in UAV-captured datasets. By retraining the DeepSORT re-identification module on aerial perspectives and integrating it with efficient detection networks, the pipeline achieved higher accuracy in vehicle recognition and improved trajectory continuity compared to baseline models.

Cao *et al*. (2021) introduced SiamAPN++, a Siamese attention-based tracking network optimized for real-time UAV deployment, improving robustness under fast motion, occlusion, and scale variation. the model incorporates attention mechanisms that refine feature aggregation, enabling more robust template matching under challenging conditions.

Wu *et al*. (2022) provided a comprehensive survey of deep learning-based UAV detection and tracking methods, highlighting CNN-based detectors, Siamese trackers, and transformer-based models while emphasizing challenges such as occlusion, computational constraints, and small object detection in aerial imagery.

Overall, the reviewed studies show that deep learning has significantly improved UAV-based target tracking by enhancing detection accuracy, identity preservation, and robustness under challenging conditions such as occlusion, scale variation, and rapid target motion. While CNN-based detectors and DeepSORT remain widely adopted, recent advances in transformer architectures, Siamese networks, reinforcement learning, and sensor fusion have further strengthened tracking performance in dynamic aerial environments. Despite these improvements, challenges related to computational constraints, small-object tracking, and maintaining consistent target identities persist. Consequently, future research is increasingly focused on developing lightweight, adaptive, and real-time tracking frameworks suitable for deployment on resource-constrained UAV platforms.

3.1.3 Traffic Monitoring and Accident Detection

Traffic monitoring and accident detection using quadcopters rely on aerial imaging and deep learning models to analyse vehicular movement and identify road incidents in real time. The process begins with data acquisition, where drones equipped with RGB or thermal cameras capture aerial video streams over highways and intersections (Byun *et al.*, 2021). Captured frames are then subjected to pre-processing operations such as video stabilization, frame extraction, resizing, and contrast enhancement to improve detection robustness under varying illumination and weather conditions (Bisio *et al.*, 2022). Deep learning–based object detectors such as YOLO (including YOLOv5 and related variants), Faster R-CNN, SSD, EfficientDet, RetinaNet, CenterNet, and transformer-based models such as DETR are commonly employed to detect vehicles, pedestrians, and road obstacles from aerial imagery (C. Chen *et al.*, 2023). Tracking methods such as DeepSORT and ByteTrack are used to maintain consistent vehicle identities across frames, enabling trajectory estimation, traffic flow analysis, and speed computation (Byun *et al*., 2021). In addition, accident detection is typically performed by analysing abnormal spatiotemporal patterns in vehicle motion, including sudden deceleration, collision events, and irregular trajectory changes, using approaches such as CNN–LSTM networks, optical-flow analysis, and other hybrid spatiotemporal learning models (Byun *et al*., 2021; Bandara *et al*., 2025). Depending on system design, inference may be carried out onboard UAVs for immediate response or offloaded to edge or cloud computing platforms for higher-resolution analysis and increased computational capacity (Byun *et al*., 2021). Performance is commonly evaluated using metrics such as precision, recall, F1-score, and inference latency to assess both detection accuracy and real-time efficiency. Overall, UAV-based traffic monitoring and accident detection systems integrate sensing, deep learning, and trajectory analysis to enable intelligent and adaptive road surveillance (Bisio *et al*., 2022; Bandara *et al*., 2025). Figure 9 shows traffic monitoring using a quadcopter.

Figure 9: Traffic monitoring (Yang *et al.*, 2025)

While the general framework described above provides a conceptual basis for UAV-based traffic monitoring and accident detection, practical implementations vary depending on sensor configurations, network architectures, and environmental conditions. Recent studies have demonstrated that integrating quadcopters with deep learning enables accurate vehicle detection, trajectory estimation, and incident recognition under diverse traffic scenarios. These implementations differ in model selection, ranging from YOLO-based detectors and two-stage CNN detectors to transformer-based architectures, as well as in computational deployment strategies, including onboard processing for real-time response and offboard processing via cloud or edge systems. The following review highlights representative studies that have successfully applied quadcopters and deep learning techniques to traffic surveillance, congestion analysis, and accident detection tasks.

Byun *et a*l. (2021) explored the use of UAV-captured imagery for traffic monitoring and proposed a deep learning framework based on convolutional neural networks (CNNs) for vehicle detection, speed estimation, and traffic flow analysis. Their approach leveraged aerial perspectives to overcome the limited coverage and blind spots associated with fixed roadside sensors. The CNN-based detection model was used to identify and classify vehicles, while trajectory estimation techniques were employed to derive vehicle speed and traffic flow metrics. Experimental results demonstrated that the UAV-based framework achieved higher accuracy and reliability than conventional ground-based monitoring systems, particularly in congested and complex traffic environments. The study highlights the potential of combining UAV imagery with deep learning to provide a scalable and flexible solution for real-time traffic analysis and intelligent transportation management.

Khanpour *et al*. (2025) proposed an intelligent UAV-based traffic surveillance framework that integrates deep learning for vehicle detection, classification, tracking, and behavioural analysis. Using aerial imagery acquired by quadcopters, the system employed object detection networks for vehicle localization, classification models to distinguish vehicle categories, and multi-object tracking algorithms to maintain trajectories across video frames. The framework further incorporated behavioural analysis modules for identifying abnormal driving patterns and traffic accidents. Experimental evaluations demonstrated high detection accuracy, robust tracking continuity, and reliable accident recognition, illustrating the effectiveness of UAV-assisted deep learning systems for smart city traffic management and rapid incident response.

Micheal *et al*. (2021) investigated deep learning-based object detection and tracking using UAV imagery for traffic monitoring, disaster management, and crowd analysis. The authors emphasized the challenges associated with aerial imagery, including scale variation, viewpoint changes, and motion blur, which differ substantially from conventional ground-level datasets. To address these issues, CNN-based detectors and tracking algorithms were adapted and fine-tuned for UAV perspectives. Experimental results showed that UAV-specific model adaptation significantly improved detection accuracy and tracking stability compared with traditional computer vision techniques. Their findings demonstrate the importance of domain-specific training for achieving robust performance in UAV traffic surveillance applications.

Yang *et al*. (2025) presented a deep learning framework for recognizing rescue activities following traffic accidents using real-time UAV video streams. The proposed approach combined convolutional neural networks (CNNs) for spatial feature extraction with recurrent architectures such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) networks for temporal sequence modelling. By analysing aerial video sequences, the framework identified rescue-related activities including victim assistance, vehicle evacuation, and emergency personnel coordination. Experimental evaluations demonstrated high recognition accuracy and robust performance under varying lighting conditions and partial occlusions, highlighting the potential of UAV-assisted deep learning systems for post-accident monitoring and emergency response.

Farhan *et al*. (2025) introduced a framework that integrates autonomous quadcopters with deep learning-based anomaly detection for real-time highway accident monitoring. The system utilized UAV mobility to provide wide-area surveillance while employing deep learning models to identify traffic anomalies such as collisions, abnormal vehicle trajectories, and congestion events. Detected incidents were automatically communicated to traffic management centres and emergency services to facilitate rapid intervention. Experimental results demonstrated faster detection times and higher accuracy than conventional monitoring infrastructures, confirming the suitability of UAV-enabled deep learning systems for intelligent transportation networks.

Ghahremannezhad *et al*. (2022) proposed a hierarchical deep learning framework for real-time accident detection using UAV imagery. The system first employed convolutional neural networks (CNNs) to detect and classify vehicles before applying a higher-level anomaly detection module to identify accident events based on collisions, abnormal stoppages, and sudden trajectory changes. By utilizing aerial viewpoints, the framework provided broader coverage than fixed roadside cameras and maintained high detection accuracy under varying traffic densities and occlusion conditions. The results demonstrate the effectiveness of hierarchical deep learning architectures for UAV-based accident detection in urban environments.

Fahim (2024) addressed vehicle detection challenges in Dhaka, Bangladesh, by fine-tuning the YOLOv9 object detection architecture on a custom dataset collected from UAV and roadside imagery. The study compared YOLOv9 against earlier versions, including YOLOv5, YOLOv7, and YOLOv8, under challenging traffic conditions characterized by heterogeneous vehicle types, high density, and severe congestion. Experimental results showed that the fine-tuned YOLOv9 model achieved superior mean Average Precision (mAP), faster inference speed, and improved robustness under varying illumination and occlusion conditions. The findings demonstrate the importance of localized model adaptation for intelligent transportation systems operating in complex urban environments.

Upadhye *et al*. (2023) presented a UAV-based framework for dynamic traffic surveillance that combines CNN and YOLO-based object detection models with vehicle tracking algorithms. Quadcopters captured real-time aerial video streams that were processed to estimate traffic density, vehicle flow, and congestion levels. The system further incorporated anomaly detection mechanisms to identify collisions, sudden stoppages, and other traffic incidents. Experimental evaluations demonstrated improved detection accuracy and response time compared with conventional monitoring systems, highlighting the advantages of integrating UAV mobility with deep learning for traffic management, accident prevention, and emergency response.

Deep learning has significantly improved UAV-based traffic monitoring through accurate vehicle detection, tracking, and traffic flow analysis. While CNN and YOLO models provide strong detection performance, transformer-based approaches offer improved contextual understanding in complex traffic environments. However, challenges such as small-object detection, occlusion, and computational limitations remain. Future research should focus on lightweight architectures and edge-computing solutions to support real-time deployment.

3.2 Agriculture

The integration of quadcopters and deep learning has significantly advanced precision agriculture by enabling automated crop monitoring, disease detection, yield estimation, and resource management. The process begins with data acquisition, where UAVs equipped with RGB, multispectral, hyperspectral, or thermal cameras capture high-resolution aerial imagery of agricultural fields (Matese and Di Gennaro, 2018). The acquired images are subsequently preprocessed through operations such as radiometric correction, image enhancement, segmentation, and vegetation index computation, including the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge Index (NDRE), to improve feature representation under varying illumination and environmental conditions (Shahi *et al.*, 2022). Deep learning models are then employed to extract meaningful information from the imagery. Convolutional Neural Networks (CNNs), YOLO-based detectors, and other classification networks are widely used for crop classification, weed identification, plant health assessment, and disease detection (Shahi *et al.*, 2023). In addition, semantic segmentation architectures such as U-Net and DeepLabV3+ provide pixel-level classification, enabling accurate delineation of crop boundaries, pest infestations, and vegetation stress zones (Li *et al.*, 2023). For applications involving temporal crop monitoring and growth assessment, recurrent architectures such as Long Short-Term Memory (LSTM) networks and 3D Convolutional Neural Networks (3D-CNNs) are employed to model spatiotemporal variations from sequential UAV imagery (Kolipaka and Namburu, 2023). Following detection and analysis, post-processing techniques are used to generate georeferenced maps, yield estimates, and decision-support information for site-specific management practices such as irrigation scheduling, fertilizer application, and pest control. By combining deep learning, remote sensing, and UAV technologies, these systems provide efficient and data-driven solutions for sustainable agricultural management (Shahi, Xu, *et al*., 2022; X. Li *et al*., 2023).

While the framework described above provides a general overview of UAV-based agricultural monitoring, practical implementations vary according to crop characteristics, sensor configurations, and deep learning architectures. Recent studies have demonstrated that integrating quadcopters with object detection, image classification, semantic segmentation, and temporal learning models enables accurate crop monitoring, disease diagnosis, weed detection, and yield prediction from aerial imagery. The following review highlights representative studies that have successfully applied these techniques in precision agriculture.

Bouguettaya *et al*. (2022) presented a comprehensive review of deep learning techniques applied to UAV imagery for agricultural crop classification. The study examined how aerial data acquired from quadcopters equipped with RGB, multispectral, and hyperspectral sensors can support precision farming applications. The authors highlighted the widespread adoption of convolutional neural networks (CNNs), ResNet architectures, U-Net segmentation networks, and YOLO-based object detectors for crop classification, weed detection, and plant health assessment. The review also emphasized the importance of preprocessing techniques, including radiometric correction and vegetation index computation such as NDVI and NDRE, as well as transfer learning strategies for adapting pre-trained models to UAV datasets with limited labelled samples. The study concluded that UAV-assisted deep learning systems provide accurate, scalable, and cost-effective solutions for crop monitoring, while identifying dataset standardization, domain adaptation, and real-time deployment as key research challenges.

Zhu *et al*. (2024) investigated the application of deep learning models to UAV imagery for crop disease and pest detection. Utilizing quadcopters equipped with RGB, multispectral, and hyperspectral sensors, the framework employed CNNs, U-Net architectures, and YOLO variants to classify diseased plants, identify pest-infested regions, and generate detailed stress maps. Experimental results demonstrated superior detection accuracy and robustness compared with traditional manual inspection and rule-based image analysis methods. The findings highlight the effectiveness of combining UAV mobility with deep learning for large-scale crop health monitoring and early disease intervention.

Karam *et al*. (2024) examined the role of quadcopters in smart agriculture, focusing on applications including crop monitoring, irrigation management, yield estimation, and farm automation. The study reviewed how UAV imagery acquired from RGB, multispectral, and thermal sensors can be integrated with deep learning models such as CNNs, U-Net, and YOLO architectures to perform crop classification, weed detection, and plant health assessment. The authors further emphasized the use of vegetation indices and georeferenced mapping techniques for precision resource allocation. Their findings demonstrate that UAV-based agricultural systems provide greater coverage, efficiency, and adaptability than traditional ground-based monitoring approaches, making them valuable tools for sustainable farming.

X. Li *et al*. (2023) proposed an enhanced semantic segmentation framework based on DeepLabV3+ for UAV remote sensing imagery. The model incorporated edge feature fusion and multi-level up-sampling strategies to improve pixel-level classification accuracy in agricultural environments characterized by complex backgrounds, occlusion, and varying illumination conditions. Compared with conventional CNN and U-Net architectures, the improved DeepLabV3+ network achieved higher mean Intersection over Union (mIoU) and segmentation accuracy, enabling more precise delineation of vegetation boundaries, pest infestations, and crop stress regions. The study demonstrates the potential of advanced semantic segmentation networks for precision agriculture applications requiring fine-grained spatial analysis.

Kolipaka and Namburu (2023) developed a hybrid deep learning framework that combines stacked bidirectional Long Short-Term Memory (BiLSTM) networks with three-dimensional convolutional neural networks (3D-CNNs) for crop yield prediction using UAV imagery. The 3D-CNN component was employed to extract spatial features from aerial images, while the BiLSTM network captured temporal variations in crop development across multiple growth stages. Experimental evaluations showed that the hybrid architecture outperformed standalone CNN and LSTM models in prediction accuracy and robustness, particularly in heterogeneous agricultural environments. The work highlights the importance of integrating spatial and temporal information for reliable yield forecasting.

Shahi *et al*. (2023) reviewed recent advances in deep learning-based crop disease detection using UAV imagery. The authors highlighted the effectiveness of CNNs, ResNet architectures, YOLO detectors, and U-Net segmentation networks for identifying disease symptoms and localizing affected crop regions from RGB, multispectral, and hyperspectral UAV data. The review also discussed challenges related to limited labelled datasets, environmental variability, and preprocessing requirements such as NDVI and NDRE computation. The study concluded that UAV-assisted deep learning systems provide highly accurate and robust disease detection capabilities, while recommending transfer learning, multimodal data fusion, and real-time deployment as important directions for future research.

Agrawal and Arafat (2024) explored the growing role of AI-enabled quadcopters in modern agriculture. The study highlighted how UAVs equipped with RGB, multispectral, hyperspectral, and thermal sensors can be integrated with CNNs, YOLO detectors, U-Net segmentation models, and transformer-based architectures for crop monitoring, weed detection, irrigation management, disease diagnosis, and yield estimation. The authors emphasized the advantages of UAV systems in providing scalable, real-time, and cost-effective monitoring solutions while identifying challenges related to dataset standardization, multimodal fusion, and domain adaptation. Their findings reinforce the importance of combining UAV technologies with advanced AI models to support intelligent and sustainable farming practices.

Tan *et al*. (2025) investigated multimodal UAV sensing for rice yield prediction by integrating hyperspectral, thermal, and LiDAR data. The study employed CNN-based architectures and transformer-based fusion models to combine biochemical, thermal, and structural crop information acquired from quadcopters. Experimental results demonstrated that multimodal fusion significantly outperformed unimodal approaches, achieving improved prediction accuracy and robustness under diverse environmental conditions. The findings suggest that integrating multiple sensing modalities with deep learning provides a scalable and highly precise solution for yield forecasting and agricultural decision support.

Khan *et al*. (2021) proposed a semi-supervised deep learning framework for crop and weed classification using UAV imagery captured by RGB-equipped quadcopters. The framework combined convolutional neural networks with semi-supervised learning strategies to exploit a small, labelled dataset alongside a larger collection of unlabelled images. Experimental evaluations demonstrated that the approach achieved high classification accuracy and outperformed fully supervised methods when labelled training data were limited. The study highlights the potential of semi-supervised learning for reducing annotation costs while enabling effective weed management and targeted herbicide application in precision agriculture.

The integration of deep learning and UAVs has enhanced crop monitoring, disease detection, weed identification, and yield prediction. CNNs, YOLO models, and segmentation networks such as U-Net and DeepLabV3+ have demonstrated strong performance across agricultural applications. Nevertheless, limited labelled datasets, environmental variability, and model generalization remain major challenges. Future efforts should emphasize transfer learning, multimodal sensing, and lightweight models for large-scale deployment.

3.3 Disaster Monitoring

Quadcopters equipped with advanced sensing technologies and deep learning models provide an effective framework for disaster monitoring by enabling rapid data acquisition and automated analysis over affected areas. During disaster events, UAVs capture high-resolution RGB, thermal, multispectral, or hyperspectral imagery, often under challenging conditions such as smoke, debris, dust, or poor visibility. The acquired data are typically pre-processed through image stabilization, noise reduction, radiometric correction, and contrast enhancement to improve feature quality before analysis.

Deep learning techniques are then employed to identify, classify, and map disaster-related features. Convolutional neural networks (CNNs) and image classification models such as ResNet, DenseNet, EfficientNet, and MobileNet are widely used to recognize damaged infrastructure and affected regions. Object detection frameworks including YOLO, Faster R-CNN, SSD, and EfficientDet are commonly applied to detect collapsed buildings, stranded individuals, damaged vehicles, and other critical targets following disasters such as earthquakes and landslides. Semantic and instance segmentation networks, including U-Net, DeepLabV3+, Mask R-CNN, and SegNet, provide pixel-level mapping of flood extents, wildfire boundaries, debris fields, and damaged structures. Furthermore, temporal deep learning architectures such as Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and 3D Convolutional Neural Networks (3D-CNNs) enable the analysis of UAV video streams for monitoring dynamic hazards, including wildfire propagation, flood progression, and post-disaster environmental changes.

The outputs generated by these models are often integrated into Geographic Information System (GIS) platforms to support emergency response, resource allocation, evacuation planning, and damage assessment. The combination of UAV mobility, high-resolution sensing, and deep learning analytics provides real-time situational awareness, scalability, and cost-effectiveness compared with conventional disaster monitoring approaches. Nevertheless, challenges remain regarding limited flight endurance, dataset annotation requirements, communication reliability, and model robustness under adverse environmental conditions. Overall, the integration of quadcopters and deep learning provides actionable intelligence across a wide range of disaster scenarios, significantly improving response efficiency and disaster resilience (Munawar *et al*., 2021; Aoki *et al*., 2022; Ghali *et al*., 2022; J. Sun *et al*., 2024; Kizilay *et al.*, 2024)

Disasters such as floods, wildfires, earthquakes, and landslides present unique monitoring challenges that require rapid, accurate, and scalable assessment methods. Owing to their ability to hover, manoeuvre through complex terrain, and capture high-resolution imagery from multiple perspectives, quadcopters have become valuable tools for disaster response operations. When integrated with deep learning models, they enable automated hazard detection, classification, localization, and mapping, providing critical information for emergency management. Flood monitoring applications primarily focus on water-body extraction and inundation mapping, wildfire monitoring emphasizes thermal anomaly detection and fire-spread prediction, earthquake response relies on structural damage assessment and victim detection, while landslide monitoring focuses on terrain deformation analysis and debris mapping. Collectively, these applications demonstrate the versatility and effectiveness of quadcopter-based deep learning systems in enhancing situational awareness, accelerating emergency response, and supporting disaster management decision-making.

3.3.1 Flood Monitoring

Floods are among the most frequent and devastating natural disasters, requiring rapid assessment of inundation zones to guide evacuation, relief operations, and infrastructure protection. Quadcopters are particularly effective in flood scenarios because they can hover at low altitudes, capture high-resolution imagery, and access areas that are otherwise unreachable during emergencies. When combined with deep learning, UAV imagery enables automated flood detection, segmentation, and damage assessment (Munawar *et al*., 2021; *Jankovic et al*., 2025). Flood monitoring with quadcopter is shown in Figure 10.

Figure 10: Flood Monitoring (Lee and Suhr, 2023)

Flood monitoring with quadcopters integrates high-resolution aerial imaging and deep learning techniques to rapidly detect and map inundated areas in real time. UAVs equipped with RGB, multispectral, thermal, or hyperspectral sensors collect detailed imagery over flood-prone regions, enabling fine-scale assessment of water extent under diverse environmental conditions (Munawar *et al*., 2021; Hernández *et al*., 2022). The captured images undergo preprocessing operations such as denoising, orthorectification, colour-space transformation, radiometric correction, and contrast enhancement to mitigate challenges associated with illumination variability, surface reflections, and sensor noise (Kumar Jangid *et al*., 2024; Simantiris and Panagiotakis, 2024). Deep learning models including CNN-based classifiers such as ResNet, DenseNet, EfficientNet, and MobileNet, object detection frameworks such as YOLO and Faster R-CNN, and semantic segmentation networks including FCN, U-Net, DeepLabV3+, SegNet, and lightweight pruned variants are widely employed to distinguish flooded from non-flooded regions and generate accurate inundation maps (Hernández et al., 2022; Lee and Suhr, 2023). Recent advances have also introduced transformer-based segmentation architectures and hybrid CNN–transformer models that improve contextual understanding and boundary delineation in complex flood environments. Several studies implement lightweight or optimized segmentation networks on embedded edge-computing hardware aboard UAVs, enabling real-time inference and transmission of compact flood masks instead of raw imagery (Lee *et al*., 2022). The resulting outputs, typically pixel-level flood segmentation maps and georeferenced inundation layers, support emergency teams in estimating flood extent, prioritizing rescue operations, and coordinating disaster response efforts (Kumar *et al*., 2024; Simantiris and Panagiotakis, 2024).

Munawar *et al*. (2021) investigated the application of deep learning to UAV-based aerial imagery for flood detection, highlighting how quadcopters can rapidly capture high-resolution images of inundated regions and provide real-time situational awareness. The study employed convolutional neural networks (CNNs) to automatically distinguish flooded from non-flooded areas, demonstrating that UAV imagery combined with deep learning significantly improves the speed and accuracy of flood mapping compared to traditional manual methods. Experimental results showed that CNN-based models achieved high detection accuracy, enabling precise delineation of flood boundaries, and supporting emergency planners in evacuation and resource allocation. The study demonstrated that UAV-based deep learning systems can deliver accurate and timely flood maps, thereby enhancing disaster response and resilience.

Mou *et al.* (2025) proposed a framework that leverages UAV imagery and advanced deep learning models to improve flood monitoring. The study evaluated U-Net, ResNet, and DeepLabV3 architectures for pixel-wise water segmentation, demonstrating that deep learning significantly outperforms traditional thresholding methods in delineating flood boundaries. High-resolution UAV imagery was preprocessed and subsequently used as input to these models to generate precise flood extent maps. Results showed that DeepLabV3 achieved the highest segmentation accuracy, while U-Net offered faster inference suitable for real-time applications.

Their results highlight DeepLabV3 as the most accurate segmentation model, while U-Net provides a practical balance between accuracy and computational efficiency for operational flood monitoring.

U. Iqbal *et al*. (2023) provide a comprehensive overview of research trends in the use of UAVs, particularly quadcopters, for flood disaster management. By analysing publications indexed in Scopus and Web of Science, the authors identified a sharp rise in drone-based flood studies since 2015, reflecting their growing importance in real-time monitoring and mapping. The review highlights that most studies employ computer vision and deep learning models such as CNNs, U-Net, and DeepLab for water segmentation and flood detection, often integrated with GIS platforms for decision support. It also notes that research is concentrated in flood-prone regions such as South Asia, China, and Europe, while challenges including limited UAV endurance, regulatory restrictions, and the need for annotated datasets remain barriers to wider adoption. The review indicates that UAVs combined with deep learning are becoming mainstream tools for flood monitoring, with emerging opportunities in multi-sensor systems, swarm coordination, and transformer-based architectures.

Lee et al. (2023) proposed a real-time monitoring system that uses quadcopter UAVs equipped with deep learning-based semantic segmentation networks to detect and map hazards such as floods and forest fires. Their work focused on network slimming techniques, which reduce the computational complexity of segmentation models such as U-Net and DeepLab, making them lightweight enough for deployment on edge devices mounted on UAVs. By optimizing these models, the system achieved high segmentation accuracy while maintaining real-time performance, enabling onboard image processing without reliance on cloud servers. This approach ensures rapid hazard detection even in environments with limited connectivity, providing emergency responders with immediate flood extent or fire boundary maps. The study demonstrates that lightweight segmentation networks can enable practical onboard disaster monitoring without sacrificing detection performance.

Lenka *et al*. (2022) investigated the challenge of cross-geography generalization in flood detection using aerial imagery and machine learning methods. The study emphasized that models trained on UAV images from one geographic region often struggle to generalize when applied to flood scenarios in different terrains or climatic conditions. To address this challenge, the authors evaluated several machine learning approaches, including convolutional neural networks and ensemble classifiers, on datasets collected from diverse flood-prone regions. Their experiments demonstrated that while CNNs achieved high accuracy within the training geography, performance declined significantly when tested on unseen regions, highlighting the importance of domain adaptation. The authors proposed strategies such as transfer learning, data augmentation, and multi-region training to improve robustness across geographic locations. The study underscores the need for geographically diverse datasets and adaptive learning techniques to achieve scalable global flood-monitoring systems.

Hashemi-Beni and Gebrehiwot (2021) introduced an integrated approach for flood extent mapping that combines deep learning segmentation with region-growing algorithms applied to UAV optical imagery. Their method employs convolutional neural networks to initially classify water pixels, which are subsequently refined using region-growing techniques to improve boundary precision and eliminate misclassifications. UAVs provided high-resolution optical data, enabling detailed mapping of inundated areas in both urban and rural environments. The study demonstrated that this hybrid approach outperformed standalone deep learning and conventional image-processing methods, achieving higher accuracy in delineating flood boundaries. The findings suggest that integrating deep learning with region-growing techniques provides a robust and cost-effective solution for flood extent mapping and disaster response.

Hernández *et al.* (2022) developed a real-time flood detection system that integrates UAV imagery with deep learning-based image segmentation models deployed on an edge-computing platform. The motivation was to overcome the limitations of cloud-based processing in disaster zones, where poor connectivity and latency can delay critical decisions. Their framework used UAVs equipped with cameras to capture aerial imagery, which was processed directly onboard using lightweight segmentation networks optimized for edge devices. The authors evaluated several architectures, including variants of U-Net and SegNet, in terms of accuracy, inference speed, and computational efficiency. Results showed that edge-based segmentation achieved near real-time performance, with detection accuracies comparable to cloud-based solutions but with significantly reduced response times. The results confirm that edge-based deep learning can provide reliable flood monitoring in disaster zones where communication infrastructure is limited.

Kumar et al. (2024) introduced a novel neural-network framework for identifying flood-affected regions using UAV-captured imagery. Their approach focused on designing a lightweight yet robust deep learning model capable of distinguishing flooded from non-flooded zones with high precision. The study emphasized the importance of optimizing neural network architectures to balance detection accuracy with computational efficiency, making them suitable for real-time deployment on UAV platforms. Experimental results showed that the proposed framework achieved superior classification performance compared with conventional CNNs, particularly in environments where water boundaries were irregular or partially obscured. The study highlights the potential of lightweight neural networks for rapid flood mapping and real-time emergency decision support.

Wienhold *et al*. (2023) developed a UAV-based multispectral remote-sensing platform for flood inundation and depth mapping, aiming to improve the accuracy and timeliness of flood monitoring. Their approach combined UAV imagery with multispectral sensors to capture detailed spectral information across affected regions, which was subsequently processed using machine learning and hydrological models to estimate both flood extent and water depth. The study demonstrated that multispectral data provided significant advantages over standard RGB imagery, particularly in distinguishing water from visually similar surfaces such as wet soil and vegetation. Field experiments confirmed that the system could generate high-resolution flood maps and reliable depth estimates, offering actionable insights for emergency response and flood-risk management. The study highlights the value of multispectral UAV sensing for accurate flood extent and depth estimation in disaster-management applications.

Zheng *et al*. (2023) presented a deep semantic segmentation framework for UAV remote-sensing imagery using a Fully Convolutional Network (FCN). Their study focused on improving pixel-level classification of aerial images to accurately delineate flooded regions, damaged infrastructure, and other disaster-related features. By leveraging FCN architectures, the authors achieved end-to-end segmentation without requiring handcrafted features, enabling more efficient processing of UAV data. The methodology involved training the FCN on diverse UAV datasets and evaluating its performance against conventional segmentation approaches. Results showed that the FCN delivered higher segmentation accuracy and robustness, particularly in complex environments characterized by heterogeneous terrain and irregular boundaries. The findings demonstrate that FCN-based semantic segmentation provides an effective and scalable solution for UAV-based disaster monitoring.

Z. Wu *et al*. (2024) proposed a transformer-based deep learning framework for extracting floodwater regions from UAV ortho-imagery. Their work addressed the limitations of conventional CNNs by leveraging the transformer's ability to capture long-range dependencies and contextual relationships within aerial images. The methodology involved training a vision transformer architecture on UAV datasets to segment floodwater areas with high precision, particularly in complex environments where water boundaries are obscured by vegetation, infrastructure, or terrain variability. Comparative experiments showed that the transformer model achieved higher accuracy and robustness than traditional CNN-based approaches while also improving generalization across diverse flood scenarios. The findings suggest that transformer-based segmentation architectures offer a promising direction for future UAV-based flood-monitoring systems, particularly in complex and heterogeneous environments.

Deep learning-based semantic segmentation has substantially improved the accuracy of UAV flood monitoring. Models such as U-Net, FCN, and DeepLabV3+ provide detailed flood extent mapping and outperform traditional image-processing techniques. However, model performance often varies across different geographical regions and environmental conditions. Improving generalization and supporting real-time deployment remain important research directions.

3.3.2 Earthquake Damage Assessment

Recent research on earthquake damage assessment has increasingly focused on the integration of quadcopter UAVs with deep learning techniques to automate post-disaster analysis. Equipped with cameras and sensors, UAVs can rapidly capture high-resolution imagery of affected areas, which is then processed using models such as convolutional neural networks (CNNs) and semantic segmentation networks to classify damaged and intact structures *(Takhtkeshha et al.*, 2023; Zou *et al.*, 2024). Transfer-learning approaches employing pretrained architectures such as ResNet, VGG, and EfficientNet have been adapted to earthquake datasets to improve classification accuracy (Kizilay *et al.*, 2024; Alsaaran and Soudani, 2025), while edge-computing solutions enable real-time damage detection directly onboard UAVs, reducing latency and dependence on cloud infrastructure (Hewawiththi *et al.*, 2024). Studies also highlight the value of integrating UAV imagery with Geographic Information System (GIS) platforms to map damage severity across urban environments. Despite challenges such as dataset annotation, occlusions in dense environments, and limited generalization across diverse earthquake scenarios, findings consistently show that UAV-based deep learning pipelines significantly reduce assessment time compared with manual surveys, achieving accuracies often exceeding 85–90% in classifying collapsed or partially damaged buildings (Tennant *et al.*, 2024). his capability enables emergency responders to prioritize rescue operations more effectively, making UAV imagery combined with deep learning a scalable and cost-effective solution for earthquake damage assessment and disaster response.

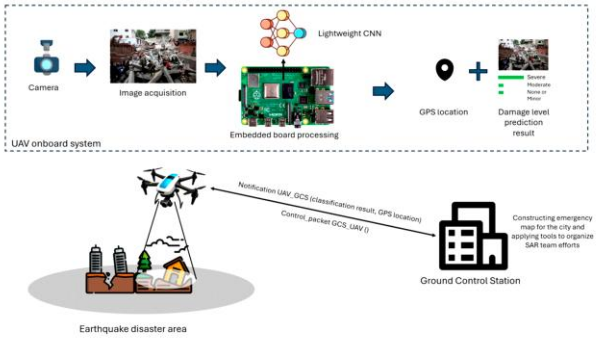

Figure 11: UAV real-time damage classification with lightweight CNNs (Alsaaran and Soudani, 2025)

Takhtkeshha *et al.* (2023) proposed a self-supervised deep learning framework for rapid post-earthquake damage detection using UAV-derived orthophotos and digital surface models (DSMs). Unlike traditional supervised methods that require extensive labelled datasets, their approach leverages self-supervised learning to minimize annotation needs while still achieving high accuracy. The system classifies building damage into four levels of severity—from no damage to complete collapse—providing detailed and actionable maps for emergency responders. By combining high-resolution UAV imagery with DSMs, the framework enhances structural differentiation and boundary precision, enabling more reliable detection of collapsed or partially damaged buildings. Results from the case study in Sarpol-e Zahab, Iran, demonstrated that the method significantly reduces mapping time and cost compared to conventional supervised pipelines, while maintaining strong classification performance. The authors conclude that self-supervised UAV-based damage detection offers a scalable, efficient, and practical solution for rapid earthquake response and recovery planning.

Alsaaran and Soudani (2025) developed a deep learning framework that uses UAV-captured imagery to classify post-earthquake building damage into multiple severity levels. Their approach integrates lightweight convolutional neural networks optimized for UAV deployment, enabling efficient processing of aerial images in disaster zones. The system predicts damage categories ranging from minor cracks to complete structural collapse, providing rapid and detailed assessments for emergency responders. By focusing on image-based classification, the framework reduces reliance on manual surveys and accelerates decision-making in post-disaster contexts. Experimental results demonstrated that the models achieved high accuracy in distinguishing damage levels, while maintaining computational efficiency suitable for UAV platforms. The authors concluded that UAV-based deep learning classification offers a scalable and practical solution for real-time earthquake damage mapping, supporting faster rescue prioritization and urban recovery planning.

Tennant *et al.* (2024) developed a deep learning pipeline to automate post-eruption building damage assessment caused by volcanic tephra fall, leveraging UAV imagery for rapid and safe data collection. The study established a damage state framework tailored to tephra hazards and used it to annotate approximately 50,000 building bounding boxes across 2,000 structures from 2,811 UAV optical images. Convolutional neural networks (CNNs) were trained to classify buildings into different damage categories, ranging from unaffected to severely impacted. The results demonstrated that UAV imagery combined with CNNs can achieve high accuracy in detecting and categorizing damage, significantly reducing the time and labour required compared to manual surveys. Importantly, the framework enables scalable and repeatable assessments, supporting emergency response and recovery planning in volcanic regions. The authors concluded that UAV-based CNN classification offers a cost-effective, rapid, and reliable solution for tephra-fall damage mapping, with potential applicability to other natural hazards.

Hewawiththi *et al.* (2024) proposed a UAV-based framework for natural disaster damage assessment that integrates semantic feature extraction with onboard data reduction to enable real-time analysis in resource-constrained environments. Their approach leverages deep learning models to extract semantic features from UAV imagery, classifying damaged versus intact structures while simultaneously reducing data transmission requirements through onboard processing. This design addresses the challenges of limited bandwidth and connectivity during disaster response, allowing UAVs to deliver actionable insights without relying heavily on cloud infrastructure. The study demonstrated that semantic extraction combined with onboard reduction significantly improves efficiency, enabling rapid and reliable damage mapping across diverse disaster scenarios. The authors concluded that this method enhances the practicality of UAV-based disaster monitoring, offering a scalable solution for real-time, low-latency damage assessment in emergency contexts.

Zou *et al*. (2024) introduced an improved instance segmentation method for rapid post-earthquake building damage assessment using UAV imagery. Their framework enhances conventional Mask R-CNN by optimizing feature extraction and refining boundary detection, which allows for more precise identification of collapsed and partially damaged structures in dense urban environments. The model was designed to be lightweight and efficient, enabling faster inference suitable for near real-time deployment during disaster response. Tested on UAV datasets from earthquake-affected areas, the approach achieved higher accuracy and Intersection-over-Union (IoU) scores than baseline segmentation models, while also reducing processing time. By producing detailed building-level damage maps, the method supports emergency responders in prioritizing rescue and recovery operations. The authors concluded that combining UAV imagery with advanced instance segmentation offers a scalable, accurate, and time-critical solution for earthquake damage assessment.

Kizilay *et al*. (2024) investigated the use of fine-tuned deep learning models for real-time earthquake damage detection using UAV imagery. Their study focused on adapting pretrained architectures such as VGG16 and ResNet through transfer learning, enabling efficient classification of damaged versus intact structures in drone-captured images. By fine-tuning these models on earthquake-specific datasets, the authors demonstrated that accuracy improved significantly compared to training from scratch, while computational efficiency was maintained for near real-time deployment. The framework was tested on diverse post-earthquake UAV datasets, achieving strong performance in identifying collapsed and partially damaged buildings. Importantly, the study highlighted the balance between model accuracy and inference speed, showing that fine-tuned CNNs can deliver actionable results quickly enough to support emergency response operations. The authors concluded that UAV imagery combined with fine-tuned deep learning offers a scalable, cost-effective, and rapid solution for earthquake damage assessment, reducing reliance on manual surveys and accelerating disaster management workflows.

Calantropio *et al.* (2021) presented a framework for automatic building damage assessment in post-disaster scenarios using UAV photogrammetry combined with deep learning techniques. Their approach employed convolutional neural networks (CNNs) to classify building damage levels directly from high-resolution UAV imagery, reducing reliance on manual surveys. The study validated the method on real disaster datasets, showing that UAV-based deep learning pipelines can achieve high accuracy in distinguishing damaged versus intact structures, while also producing rapid, scalable maps suitable for emergency response. Major findings highlighted that integrating UAV data with automatic segmentation and classification not only accelerates damage mapping but also improves consistency compared to traditional field assessments. The authors concluded that this approach provides a cost-effective, reliable, and time-critical solution for disaster management agencies, enabling faster prioritization of rescue and recovery operations in complex urban environments.

Martinelli *et al*. (2023) presented a method for structural damage detection and localisation using UAV imagery combined with object detection algorithms. The study employed YOLO-based models to automatically identify and localise damaged areas on buildings from drone-captured images. The framework was tested on diverse datasets representing different building types and damage conditions, demonstrating that UAV imagery processed with deep learning can achieve high accuracy in detecting cracks, collapses, and other structural failures. Importantly, the system not only classified damage but also provided precise localisation, enabling responders to map affected structures quickly and consistently. The authors concluded that integrating UAVs with object detection models offers a scalable, efficient, and reliable solution for post-disaster damage assessment, reducing reliance on manual surveys and accelerating emergency response workflows.

Xia *et al*. (2023) developed a deep learning application for building damage detection following the devastating February 2023 Turkey earthquakes, leveraging ultra-high-resolution remote sensing imagery. Their framework employed convolutional neural networks (CNNs) trained on UAV and satellite datasets to automatically classify buildings into different damage levels, ranging from intact to collapsed. By fine-tuning pretrained models and integrating contextual features, the system achieved high accuracy in large-scale damage mapping, outperforming traditional manual surveys in both speed and consistency. The study emphasized the importance of rapid, automated assessment for humanitarian relief, showing that deep learning can provide actionable insights within hours of a disaster. Major findings highlighted that combining UAV imagery with deep learning enables scalable, cost-efficient, and reliable damage detection, supporting emergency responders in prioritizing rescue and recovery operations across wide urban areas.

From the reviewed studies, it is evident that recent advances in earthquake damage assessment increasingly rely on the integration of quadcopter UAVs with deep learning techniques to automate post-disaster analysis. Various approaches, including convolutional neural networks (CNNs), transfer learning with pretrained architectures such as ResNet and VGG, object detection models such as YOLO, and instance segmentation frameworks such as Mask R-CNN, have demonstrated strong performance in identifying and classifying damaged structures. Self-supervised learning methods further reduce dependence on large, annotated datasets, while onboard feature extraction and edge-computing strategies enable near real-time damage assessment in resource-constrained environments. In addition, UAV photogrammetry and high-resolution imagery provide detailed spatial information that improves damage localization and severity mapping. Overall, the reviewed literature demonstrates that UAV imagery combined with advanced deep learning models offers a fast, scalable, accurate, and cost-effective solution for earthquake damage assessment, significantly reducing assessment time and supporting emergency responders in prioritizing rescue, recovery, and reconstruction efforts.

Deep learning has accelerated post-earthquake damage assessment by enabling automated building classification and damage mapping from UAV imagery. Transfer learning and segmentation approaches have improved accuracy while reducing dependence on extensive training data. Despite these advances, challenges related to dataset availability, structural occlusions, and model generalization persist. Future research should focus on lightweight and adaptive models suitable for real-time disaster response.

3.3.3 Wildfire Monitoring

Wildfires represent one of the most severe environmental threats, causing widespread ecological damage, economic losses, and risks to human life. Traditional monitoring methods, such as satellite imaging and ground-based sensors, often suffer from limitations in spatial resolution, coverage, and response time, making them less effective for early detection and continuous tracking. In recent years, the integration of deep learning techniques with quadcopter UAVs has emerged as a promising solution to overcome these challenges. UAVs provide flexible, high-resolution aerial imagery, while deep learning models enable automated analysis of complex visual data, allowing for the rapid identification of fire, smoke, and other wildfire indicators. Researchers have explored diverse approaches ranging from CNN-based smoke and flame detection (S. Y. Kim and Muminov, 2023; Rasel Rahman *et al.*, 2023) to YOLO- and transformer-based architectures for real-time classification and segmentation (Ghali *et al.*, 2022; Shamta and Demir, 2024) as well as reinforcement learning strategies for UAV coordination and fire-front tracking (Viseras and Marchal, 2025). Lightweight CNNs optimized through hierarchical multi-task knowledge distillation have further advanced the field by enabling efficient real-time inference on resource-constrained UAV platforms (El-Madafri *et al.*, 2024). Collectively, these developments highlight a clear trend in wildfire monitoring research: leveraging UAV mobility and the analytical capabilities of deep learning to create adaptive, scalable, and real-time systems that can provide emergency responders with timely and actionable intelligence.

Mashraqi *et al*. (2022) presented a comprehensive framework for leveraging UAVs in wildfire monitoring. They emphasized that traditional fire detection methods such as satellites or ground sensors often suffer from delays, low spatial resolution, or limited coverage, making them inadequate for rapid response. To address this, they deployed drones equipped with high-resolution cameras to capture aerial imagery of forested regions and designed a modified convolutional neural network (CNN) architecture tailored for fire detection. The model incorporated enhancements such as optimized convolutional layers and fine-tuned hyperparameters to improve classification accuracy while reducing false positives caused by confounding factors like smoke, fog, shadows, or bright sunlight. Extensive experiments demonstrated that the modified CNN achieved significantly higher detection accuracy compared to baseline models, with improved robustness across varying environmental conditions. Importantly, the system was computationally efficient, enabling real-time inference directly on UAV platforms, which is critical for early warning and rapid hazard mapping. The findings underscored that integrating UAV imagery with optimized deep learning models provides a scalable, cost-effective, and reliable solution for forest fire detection, offering emergency responders actionable intelligence to minimize damage and protect ecosystems. The study concluded that such UAV-based systems can complement or even surpass satellite monitoring by delivering timely, localized, and high-resolution fire detection capabilities.

El-Madafri *et al*. (2024) proposed a deep learning framework designed to balance accuracy with computational efficiency for wildfire monitoring. The authors employed a teacher–student knowledge distillation approach, where a large, high-capacity CNN acted as the teacher and a lightweight CNN as the student. Through hierarchical multi-task distillation, the student network learned not only the final classification outputs but also intermediate feature representations, improving generalization and robustness. UAV and aerial imagery datasets of forest fires were used to train and validate the models, with tasks including both fire and smoke detection. Experimental results showed that the lightweight CNN achieved competitive accuracy compared to heavier models while drastically reducing computational demands, enabling real-time inference on UAVs and embedded devices. The major finding was that combining lightweight CNNs with hierarchical multi-task knowledge distillation provides a scalable, efficient, and accurate solution for real-time forest fire detection, making it practical for deployment in disaster monitoring systems where speed and resource constraints are critical.

Viseras *et al*. (2025) proposed a cooperative UAV system designed to track wildfire spread in real-time by applying reinforcement learning techniques. The authors developed a simulation environment to model fire dynamics and deployed multiple UAVs virtually to monitor the advancing fire front. Using deep Q-learning, each UAV learned optimal flight strategies through trial-and-error interactions, enabling them to self-organize and coordinate coverage without central control. This methodology allowed UAVs to adapt dynamically to changing fire conditions, optimizing trajectories to minimize monitoring gaps and maximize efficiency. The findings showed that the system successfully maintained continuous surveillance of wildfire fronts, demonstrated scalability with larger UAV teams, and provided timely situational awareness that could support emergency responders. The major contribution was the demonstration that reinforcement learning can enable autonomous UAV teams to deliver efficient, adaptive, and real-time wildfire monitoring, complementing traditional detection systems with continuous hazard tracking.

Ghali *et al*. (2022) explored advanced neural architectures to improve the accuracy and robustness of wildfire monitoring using aerial imagery captured by UAVs. The authors recognized that conventional CNNs, while effective, often struggle with complex wildfire scenes where smoke, flames, and background vegetation overlap. To address this, they developed a framework that combined ensemble deep learning models (EfficientNet-B5 and DenseNet-201) with transformer-based architectures for both classification and segmentation tasks. UAV imagery datasets were used to train and validate the models, focusing on distinguishing fire regions from non-fire areas and segmenting boundaries with high precision. The methodology emphasized leveraging transformers' ability to capture long-range dependencies and contextual relationships within images, complementing CNNs' strength in local feature extraction. Experimental results showed that the hybrid approach achieved higher accuracy and generalization than standalone CNNs, reducing false positives and improving segmentation quality in diverse wildfire scenarios. The major finding was that integrating deep learning ensembles with transformer models provides a scalable, powerful solution for UAV-based wildfire classification and segmentation, enabling more reliable hazard mapping and supporting faster, data-driven emergency response.

Kim and Muminov (2023) investigated the use of UAV-captured aerial imagery combined with deep learning models to detect smoke as an early indicator of forest fires. Recognizing that smoke often appears before flames are visible, the authors emphasized the importance of early detection for minimizing wildfire damage. Their methodology involved deploying quadcopter UAVs equipped with cameras to collect high-resolution images of forested areas, which were then processed using convolutional neural networks (CNNs) trained to classify smoke versus non-smoke scenes. The models were designed to handle environmental challenges such as haze, clouds, and varying illumination, which can easily cause false alarms. Experimental results showed that the CNN-based system achieved high detection accuracy and robustness, outperforming traditional image processing techniques and reducing false positives. The findings demonstrated that UAV-based smoke detection systems can operate in real time, providing emergency responders with actionable intelligence to intervene before fires escalate. The major contribution of the study was to show that integrating UAV imagery with deep learning enables scalable, efficient, and reliable early wildfire detection, complementing flame-based detection methods and enhancing overall disaster monitoring capabilities.

Shamta and Demir (2024) presented a framework that integrates UAV imagery with advanced deep learning models to provide real-time wildfire surveillance. The authors recognized that traditional fire detection methods are limited by slow response times and low spatial resolution, so they proposed a UAV-based system capable of capturing high-resolution aerial images and processing them with state-of-the-art deep learning algorithms such as YOLOv5, YOLOv8, and CNN-RCNN. Their methodology involved training these models on datasets of fire and non-fire scenes to classify and localize fire outbreaks accurately. The UAVs served as mobile surveillance units, transmitting imagery to the detection system for rapid analysis. Experimental results showed that the deep learning models achieved high detection accuracy and robustness, with YOLO architectures excelling in real-time performance and CNN-RCNN providing strong precision in complex environments. The findings demonstrated that UAV-based surveillance systems can deliver scalable, efficient, and reliable fire detection and monitoring, offering emergency responders timely intelligence to minimize damage and improve response strategies. The major contribution of the study was to show that combining UAV mobility with deep learning detection frameworks creates a powerful, real-time surveillance solution for forest fire management.

Rasel *et al*. (2023) examined how UAVs equipped with cameras can be combined with deep learning models to improve wildfire detection. The authors highlighted the limitations of traditional monitoring systems, such as satellites with low temporal resolution and ground sensors with restricted coverage, and proposed UAVs as a flexible, high-resolution alternative. Their methodology involved deploying quadcopter UAVs to capture aerial imagery of forested regions and training deep convolutional neural networks (CNNs) to classify fire versus non-fire scenes. The CNN architecture was optimized to handle environmental challenges such as smoke, haze, shadows, and varying illumination, which often lead to false alarms. Experimental results demonstrated that the UAV-assisted CNN system achieved high detection accuracy and robustness, outperforming conventional image processing methods. Importantly, the model was computationally efficient enough to support real-time inference, making it suitable for deployment during active wildfire scenarios. The major finding was that integrating UAV imagery with deep CNNs provides a scalable, reliable, and efficient solution for forest fire detection, offering emergency responders timely intelligence to minimize damage and enhance response strategies.

Diaz-Vilor et al. (2025) proposed a novel framework for using multiple UAVs collaboratively to track wildfire spread in real time. The authors recognized that wildfires are highly dynamic and unpredictable, requiring continuous monitoring across large areas, which single UAVs or static sensors cannot achieve efficiently. Their methodology employed reinforcement learning (RL), specifically multi-agent RL algorithms, to train UAV swarms to coordinate their movements and maintain effective coverage of the fire perimeter. Each UAV acted as an autonomous agent, learning optimal flight paths through trial-and-error interactions with the simulated wildfire environment, while also considering the positions and actions of other UAVs to avoid redundancy and maximize efficiency. The findings showed that UAV swarms guided by RL could adapt dynamically to changing fire conditions, achieve robust coverage of the fire front, and scale effectively with larger numbers of UAVs. The major contribution of the study was to demonstrate that reinforcement learning enables UAV swarms to provide efficient, adaptive, and decentralized wildfire tracking, offering emergency responders timely situational awareness and complementing detection systems with continuous hazard monitoring.

The combination of UAVs and deep learning has improved wildfire detection, smoke recognition, and fire-front monitoring. CNNs, YOLO architectures, and transformer-based models provide reliable detection performance, while reinforcement learning supports autonomous wildfire tracking. However, environmental variability and computational constraints continue to affect system reliability. Future developments should prioritize multimodal sensing and coordinated multi-UAV monitoring systems.

3.3.4 Landslide Monitoring

Landslides are among the most destructive natural hazards, causing severe damage to infrastructure, ecosystems, and human lives, and their effective monitoring remains a critical challenge in disaster risk management. Traditional methods such as satellite imaging and ground surveys often suffer from limitations in spatial resolution, coverage, and timeliness, making them less effective for early detection and continuous monitoring. In recent years, the integration of deep learning techniques with quadcopter UAVs has emerged as a promising solution to overcome these challenges. UAVs provide flexible, high-resolution aerial imagery, while deep learning models enable automated analysis of complex terrain features, allowing for the rapid identification of landslide indicators such as cracks, slope failures, and unstable soil. Comparative studies have demonstrated the effectiveness of CNNs and other deep learning models in detecting landslides and sinkholes from UAV imagery (Kariminejad *et al.*, 2024) while systematic reviews highlight UAVs as powerful tools for landslide investigation and monitoring when integrated with AI (Sun *et al.*, 2024). Case studies further confirm the utility of UAV imagery combined with CNNs for automated landslide detection (Vu *et al.*, 2021), and high-resolution UAV imagery has been successfully used with AI models to automatically detect and map landslide cracks (Sandric *et al.*, 2024). Deep learning applied to UAV datasets has also proven effective in complex terrains, including the Baihetan Reservoir area, where challenging topography complicates landslide monitoring (Li *et al.*, 2024), while broader reviews emphasize opportunities for lightweight models, multi-sensor integration, and improved generalization across diverse landscapes (Chandra and Vaidya, 2024; Zhang and Wang, 2024). More recent surveys underscore the potential of UAV-based deep learning systems for scalable landslide identification and early-warning applications (Jiang and Mei, 2026). Collectively, these studies demonstrate that combining UAV mobility with the analytical capabilities of deep learning offers a promising pathway toward efficient, adaptive, and real-time landslide monitoring systems capable of providing emergency responders and decision-makers with timely and actionable intelligence.

Kariminejad *et al*. (2024) evaluated multiple deep learning architectures for landslide and sinkhole detection using high-resolution UAV imagery collected over semi-arid regions prone to slope instability. UAVs were deployed to acquire imagery over semi-arid regions prone to slope instability, and multiple deep learning architectures, including convolutional neural networks (CNNs) and other advanced classifiers, were trained and evaluated for automatic detection of landslide and sinkhole features. The study compared model performance in terms of accuracy, robustness, and sensitivity to environmental challenges such as varying terrain textures and illumination conditions. Results demonstrated that deep learning approaches significantly outperformed traditional image analysis methods, with CNN-based models achieving high precision in identifying landslide boundaries and sinkhole structures. The authors concluded that integrating UAV imagery with deep learning provides a scalable and reliable solution for hazard detection, supporting early warning systems and disaster risk management in vulnerable landscapes.

J. Sun *et al*. (2024) provided a comprehensive review of UAV applications in landslide research, with particular emphasis on the role of deep learning in automating detection and monitoring tasks. The review examined UAV-based approaches across different stages of landslide management, including pre-event risk assessment, real-time monitoring, and post-event damage evaluation. The authors highlighted how UAVs provide high-resolution imagery and flexible deployment in difficult terrain, while deep learning models such as CNNs, YOLO, and transformer architectures enable accurate landslide classification, crack detection, and boundary segmentation. The review found that UAV-based deep learning approaches significantly improve the accuracy and efficiency of landslide monitoring compared with conventional remote sensing methods, reducing false alarms and enhancing early warning capabilities. The authors concluded that combining UAV mobility with AI-driven analysis creates scalable systems capable of adapting to diverse environments, making them valuable tools for disaster risk reduction.

Vu *et al*. (2021) explored the use of UAVs for identifying and monitoring landslide activity through aerial imagery and deep learning techniques. Quadcopter UAVs were used to capture high-resolution images of landslide-prone terrain, which were subsequently analysed using CNN-based models for automatic landslide detection and classification. The study highlighted the advantages of UAVs in accessing hazardous and difficult-to-reach areas while providing rapid and flexible data acquisition compared with traditional ground surveys and satellite observations. Results indicated that the UAV-based deep learning system achieved high accuracy in delineating landslide boundaries and distinguishing unstable areas from stable terrain. The authors concluded that UAV imagery combined with deep learning offers a scalable and reliable solution for landslide monitoring, supporting early warning systems and improving disaster risk management strategies.

Sandric *et al.* (2024) investigated the application of UAVs and deep learning for the detection of early indicators of slope instability. High-resolution aerial imagery acquired by quadcopter UAVs was analysed using CNN-based models to automatically identify and map surface cracks that often precede landslide events. The system was trained to distinguish genuine cracks from confounding features such as shadows, vegetation, and surface irregularities. Results demonstrated high detection accuracy and reliable mapping of potential landslide zones. The authors concluded that integrating UAV imagery with deep learning provides an efficient and scalable approach for continuous slope monitoring and early warning of landslide hazards.

Z. H. Li *et al*. (2024) examined the use of UAV imagery and deep learning for landslide identification in the Baihetan Reservoir region, an area characterized by complex terrain and frequent slope instability. High-resolution UAV datasets were analysed using CNN-based and other deep learning models to classify landslide features. The study incorporated preprocessing techniques to address challenges associated with vegetation cover, heterogeneous soil textures, and varying illumination conditions. Results showed that the deep learning framework achieved robust recognition performance and outperformed conventional image analysis methods. The authors concluded that UAV-based deep learning systems provide reliable, scalable, and effective monitoring solutions for landslide-prone regions, supporting early warning and disaster risk management efforts.

Chandra and Vaidya (2024) presented a comprehensive review of deep learning applications in landslide monitoring, highlighting UAV imagery as an important source of high-resolution data. The review examined the use of CNNs, transformer models, and hybrid architectures for landslide detection, boundary segmentation, and crack identification. The authors emphasized that UAVs enable flexible and detailed observation of landslide-prone areas, while deep learning facilitates automated interpretation of complex terrain features. The review found that deep learning methods consistently outperform traditional image processing approaches in terms of accuracy and robustness. Future research directions identified include lightweight models for real-time UAV deployment, improved model generalization across landscapes, and integration of multisensor data for comprehensive hazard assessment.

Zhang and Wang (2024) reviewed deep learning frameworks for landslide monitoring, focusing on the integration of UAV imagery with remote sensing datasets and geo-environmental variables. The study discussed the application of CNNs, transformer models, and hybrid deep learning approaches for landslide detection, classification, and mapping. UAVs were highlighted as valuable tools for acquiring high-resolution imagery that complements satellite and ground-based observations. The review reported that deep learning methods significantly improve detection accuracy and robustness, particularly in complex terrains affected by vegetation cover and heterogeneous surface conditions. The authors also identified challenges related to model generalization, computational requirements, and multisensor data fusion. Overall, the study concluded that UAV-based deep learning systems represent a promising pathway toward scalable and adaptive landslide monitoring.

Jiang *et al.* (2026) provided a comprehensive survey of recent advances in deep learning for landslide detection and monitoring, identifying UAV imagery as one of the most promising data sources. The review examined studies employing CNNs, transformer architectures, and hybrid models for landslide identification, terrain classification, and hazard prediction. The authors noted that UAVs provide high-resolution, flexible, and cost-effective imagery that complements satellite and ground-based observations, making them particularly suitable for rapid hazard assessment in difficult-to-access regions. The survey found that deep learning approaches consistently outperform traditional image processing and manual mapping techniques, delivering improved accuracy and robustness across diverse environmental conditions. Key challenges identified include limited labelled datasets, computational constraints for real-time UAV deployment, and the need for better model generalization across geographic regions. The authors concluded that integrating UAV imagery with deep learning offers a powerful and scalable solution for landslide detection and disaster risk reduction.

From the reviewed studies, it is evident that UAV-based deep learning systems have become effective tools for landslide monitoring and hazard assessment. CNNs, transformer models, and hybrid architectures have demonstrated strong capabilities in detecting landslide boundaries, identifying surface cracks, and classifying unstable terrain from high-resolution UAV imagery. The literature further highlights the advantages of UAVs in providing flexible, detailed, and cost-effective data acquisition in challenging environments. Overall, the integration of UAV imagery with deep learning offers a scalable, reliable, and efficient approach for landslide detection, supporting early warning systems and enhancing disaster risk management.

UAV-based deep learning systems have demonstrated strong capabilities in landslide detection, crack identification, and hazard mapping. CNN-based methods remain dominant, while transformer architectures show promise for analysing complex terrain features. However, vegetation cover, terrain variability, and limited training datasets continue to affect model performance. Advances in transfer learning, multisensor fusion, and lightweight models are expected to improve monitoring accuracy and scalability.

4 Challenges of Integrating Deep Learning with Quadcopter Systems

The integration of deep learning techniques with quadcopter platforms introduces several technical and operational challenges that affect performance, reliability, and real-time applicability. A primary limitation is the restricted computational power and energy capacity of quadcopters, which makes it difficult for embedded processors to execute large neural networks efficiently. McEnroe *et al.* (2022) noted that high-parameter models often exceed the processing capabilities of onboard computing units, resulting in inference delays that can impair autonomous navigation and responsiveness during flight. To address these limitations, some systems offload computation to nearby edge servers. However, edge offloading introduces additional constraints, including communication latency, fluctuating bandwidth, and increased battery consumption caused by continuous data transmission.

Another challenge is the degradation of visual data quality during wireless communication, which can negatively affect model performance. Ozer *et al.* (2023) reported that UAV imagery transmitted over wireless networks is susceptible to noise, compression artifacts, and packet loss, even in advanced 5G environments. These transmission impairments can reduce detection accuracy unless communication-aware architectures or image restoration techniques are incorporated into the processing pipeline. Furthermore, efficient task allocation between onboard processors and edge servers remains a critical issue. P. Zhang *et al*., (2023) demonstrated that deep learning workloads frequently exceed the capabilities of onboard hardware, making intelligent workload partitioning strategies, often based on reinforcement learning, necessary for maintaining efficient and reliable operation.

Even when computation is performed entirely onboard, quadcopters face significant thermal and energy constraints. Jose *et al.* (2019) showed that embedded platforms such as the Jetson Nano and Raspberry Pi experience reduced inference speed and increased heat generation when executing computationally intensive convolutional neural networks (CNNs). This highlights the trade-off between model complexity, real-time performance, and flight endurance, emphasizing the need for lightweight and energy-efficient deep learning architectures.

In addition to computational challenges, object detection in UAV imagery presents several vision-related difficulties. Tang *et al.*(2024) identified challenges such as small-object detection, complex backgrounds, class imbalance, and arbitrary object orientations. Small targets, including pedestrians, vehicles, and animals, often occupy only a few pixels in high-resolution aerial images, making them difficult to detect accurately. Complex backgrounds and visually similar objects can increase false detections, while class imbalance may bias models toward dominant categories. Furthermore, objects captured from aerial viewpoints can appear at arbitrary rotations, reducing the effectiveness of conventional horizontal bounding-box detectors. To address these challenges, researchers have explored multiscale feature fusion, attention mechanisms, graph neural networks, data augmentation techniques, and rotated object detection frameworks.

Overall, the deployment of deep learning on quadcopter platforms remains constrained by limited computational resources, energy consumption, communication instability, model complexity, and challenging imaging conditions. Addressing these issues is essential for achieving reliable, efficient, and real-time intelligent quadcopter systems across diverse application domains.

4.1 Considerations in use of Quadcopter

Rotor-type unmanned aerial vehicles (UAVs), particularly quadcopters, have become valuable tools for intelligence gathering and data acquisition in remote or inaccessible environments. Their applications span precision agriculture, disaster assessment, environmental monitoring, infrastructure inspection, and security surveillance. Despite their versatility and operational flexibility, several factors must be considered to ensure effective deployment and reliable performance. Addressing these challenges can significantly improve the efficiency, safety, and accuracy of quadcopter-based operations (Vohra *et al*., 2022; Yuan *et al*., 2024).

(a) Noise Suppression

One limitation of quadcopters is the noise generated by their rotating propellers, which can reveal their presence during surveillance or monitoring missions. Excessive acoustic signatures may compromise covert operations and reduce operational effectiveness. Research efforts have therefore focused on noise reduction through improved propeller design, vibration damping materials, optimized frame configurations, and acoustic insulation techniques. Effective noise suppression contributes to improved stealth and reduced environmental disturbance.

(b) Obstacle Avoidance

Obstacle avoidance is essential for safe and autonomous quadcopter navigation. Modern quadcopters employ sensors such as ultrasonic sensors, LiDAR, radar, infrared sensors, and cameras to detect obstacles in multiple directions. Once an obstacle is identified, navigation algorithms determine an appropriate avoidance strategy, such as path replanning, altitude adjustment, or directional changes. Recent advances in artificial intelligence and computer vision have further enhanced obstacle detection and avoidance capabilities, improving flight safety in complex environments.

(c) Weather Conditions

Weather conditions significantly influence quadcopter performance and operational reliability. Factors such as strong winds, heavy rainfall, fog, and extreme temperatures can adversely affect flight stability, sensor accuracy, and communication systems. Severe weather may also damage critical components, including propellers, batteries, and flight controllers. Consequently, weather assessment is a crucial consideration during mission planning and execution.

(d) Adverse Weather Videography

Many applications require image and video acquisition under challenging environmental conditions, including night-time operations and poor visibility. Thermal cameras, infrared sensors, and stabilized imaging systems are commonly integrated into quadcopters to improve image quality in such environments. Gimbal stabilization mechanisms help maintain camera orientation and reduce motion-induced distortions, enabling consistent image capture despite environmental disturbances or drone movement.

(e) Communication Range

Reliable communication between the quadcopter and the ground control station is essential for command transmission, telemetry monitoring, and data transfer. Communication disruptions may occur when the UAV exceeds its operational range or encounters signal interference. To extend coverage, solutions such as relay drones, signal repeaters, high-gain antennas, and optimized antenna polarization techniques can be employed. These approaches improve communication reliability during long-range missions.

(f) Battery Management

Battery capacity remains one of the most significant limitations of quadcopter systems. Flight endurance is directly influenced by battery characteristics, including voltage, capacity, discharge rate, and weight. Most quadcopters rely on rechargeable lithium-polymer (LiPo) batteries, which provide high energy density but limited operational duration. Effective battery management strategies are therefore necessary to maximize flight time and ensure mission completion, particularly for long-distance or energy-intensive applications.

(g) Flight Controller

The flight controller functions as the central control unit of the quadcopter, managing flight stability, navigation, sensor integration, and control commands. It continuously processes data from onboard sensors such as accelerometers, gyroscopes, magnetometers, and GPS modules to maintain stable flight. The choice of flight controller significantly affects system performance, autonomy, and reliability. Consequently, selecting and evaluating appropriate flight controllers is an important aspect of quadcopter design and deployment.

5 Conclusion

The integration of quadcopters and deep learning has emerged as a powerful approach for real-time aerial monitoring across a wide range of applications, including security surveillance, target tracking, traffic monitoring, precision agriculture, and disaster management. Advances in deep learning architectures, ranging from convolutional neural networks and semantic segmentation models to attention-based and lightweight edge-deployable frameworks, have significantly improved the ability of UAVs to analyze complex aerial imagery with high accuracy and efficiency.

The reviewed studies demonstrate that deep learning has enhanced object detection, tracking, and scene understanding capabilities in UAV systems, enabling more reliable monitoring and decision-making in dynamic environments. In surveillance and tracking applications, deep learning models have improved detection accuracy and target localization, while in precision agriculture they have supported automated crop health assessment and disease detection. Similarly, in disaster management applications such as flood, wildfire, earthquake, and landslide monitoring, UAV-based deep learning systems have enabled rapid damage assessment, hazard detection, and situational awareness, thereby supporting more effective emergency response operations.

Despite these achievements, challenges related to limited onboard computational resources, energy constraints, communication reliability, environmental variability, and model generalization remain significant barriers to large-scale autonomous deployment. Although recent advances in lightweight neural networks, edge computing, multisensor fusion, and intelligent task offloading have shown considerable promise, further research is needed to develop more robust, scalable, and reliable UAV systems capable of operating efficiently in diverse real-world environments.

Overall, the literature demonstrates that the synergy between quadcopters and deep learning is transforming aerial monitoring by enabling intelligent, adaptive, and scalable solutions. Future research should focus on improving model efficiency, robustness, multisensor integration, communication resilience, and real-time autonomous decision-making to further enhance the practical deployment of next-generation intelligent UAV systems.

5.1 Ethical Considerations

The integration of quadcopters and deep learning raises important ethical concerns related to privacy, safety, data security, and responsible deployment. UAVs equipped with imaging sensors may capture personal or sensitive information, making compliance with privacy and data protection regulations essential. Safe operation is also critical, particularly in populated areas and disaster zones, where adherence to aviation guidelines and reliable obstacle avoidance mechanisms help minimize risks.

In addition, deep learning models may produce inaccurate results when trained on limited or biased datasets, highlighting the need for proper validation and performance evaluation. Cybersecurity measures are equally important to protect communication links and collected data from unauthorized access. Therefore, the responsible use of UAV-based deep learning systems requires careful attention to privacy, safety, reliability, and security to ensure their beneficial and ethical application.

Conflict of interest

The authors declare no conflict of interest regarding the publication of this paper.

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