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# Autonomous Drone Navigation Using Computer Vision: Challenges and Future Directions

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## ABSTRACT

*Unmanned Aerial Vehicles (UAVs), commonly known as drones, have emerged as versatile platforms revolutionizing diverse fields such as precision agriculture, environmental monitoring, infrastructure inspection, and disaster management. Their growing impact is driven by advances in autonomy that enable efficient, scalable, and intelligent operations. Among the enabling technologies, computer vision plays a pivotal role by allowing drones to perceive, interpret, and interact with their environment through visual sensing. This capability has significantly improved tasks such as obstacle detection, localization, mapping, and scene understanding, even in GPS-denied or visually degraded conditions. Despite these advances, achieving full autonomy remains a major challenge. Vision-based navigation is often hindered by adverse weather, illumination changes, dynamic obstacles, and computational limitations, alongside issues of domain shift and long-tail edge cases that compromise reliability and safety. This review paper presents a comprehensive analysis of recent progress in vision-based autonomous drone navigation, spanning classical computer vision, deep learning, and emerging paradigms such as Vision Transformers, reinforcement learning, and self-supervised learning. It further highlights open challenges and outlines future research directions, including multi-sensor fusion, domain adaptation, collaborative perception, neuromorphic computing, and explainable AI—aiming to guide the development of resilient and robust UAV systems capable of dependable real-world autonomy.*

**Keywords:** *Autonomous Drones, Computer Vision, Deep Learning, Visual Slam, Multi-Sensor Fusion, Domain Adaptation, Explainable AI, Robust Perception.*

## 1. INTRODUCTION

The proliferation of Unmanned Aerial Vehicles (UAVs), commonly known as drones, has transformed operations across numerous sectors including precision agriculture, infrastructure inspection, search and rescue operations, and last-mile delivery services [1-4]. The global drone market continues to experience exponential growth, a trend fueled by continuous advancements in hardware miniaturization, sensor technology, and autonomous control systems. Central to achieving true autonomy is the capability to perceive and

interpret complex environments, a task for which computer vision has emerged as a cornerstone technology.

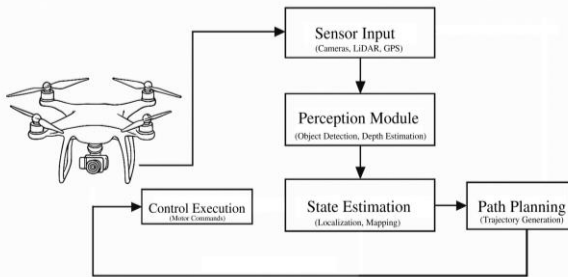
Unlike traditional navigation approaches that rely heavily on Global Navigation Satellite Systems (GNSS), vision-based navigation utilizes onboard cameras as primary sensors to understand environmental context, identify obstacles, and make real-time navigation decisions [5]. This capability proves indispensable for operation in GNSS-denied environments such as indoor spaces, under dense forest canopies, or within urban canyons where satellite signals are unreliable or unavailable. By processing rich visual data streams, drones can perform Simultaneous Localization and Mapping (SLAM), detect and track dynamic objects, and understand scene semantics, thereby replicating a level of situational awareness comparable to human pilots.

However, this reliance on visual perception introduces significant challenges that must be addressed for widespread deployment. The performance of computer vision algorithms demonstrates high susceptibility to varying environmental conditions including rapid lighting changes, adverse weather phenomena (rain, fog, snow), and the presence of dynamic obstacles [6]. Furthermore, the inherent computational constraints of UAV platforms necessitate a delicate balance between model complexity and real-time inference performance [7]. A particularly critical challenge involves the "long-tail" problem, where deep learning models trained predominantly on common scenarios perform poorly when encountering rare but safety-critical events [8]. These multifaceted challenges underscore the pressing need for robust, efficient, and generalizable vision-based navigation systems capable of operating reliably in real-world conditions.

This review paper provides a structured and comprehensive overview of the field of autonomous drone navigation using computer vision. We synthesize the current technological landscape, progressing from fundamental techniques to cutting-edge AI models, while providing critical examination of the key challenges hindering widespread practical deployment. Special emphasis is placed on the crucial issues of robustness in long-tail scenarios and adverse weather conditions. The paper further discusses current innovative solutions and outlines promising future research directions to guide the research community toward achieving truly reliable and autonomous aerial systems suitable for real-world applications.

## 2. HARDWARE AND SOFTWARE ARCHITECTURE OF DRONES

The efficacy of a vision-based autonomous drone is contingent upon a tightly integrated hardware-software stack, both designed under stringent weight, power, and computational constraints. To visualize the typical workflow of such a system, **Figure 1** presents a high-level pipeline, illustrating the flow from sensor data to actuator commands.



**Figure 1:** A Typical Pipeline for Vision-Based Autonomous Drone Navigation.

A clear understanding of the perception-to-control sequence is fundamental to vision-based drone autonomy. As illustrated in **Figure-1**, the navigation process begins with sensor data acquisition, which is then interpreted through perception modules responsible for environmental understanding and obstacle detection.

The derived environmental model feeds into state estimation, allowing the drone to localize itself accurately before executing path planning and control.

This modular flow demonstrates how autonomy emerges from the tight coupling between sensing, perception, and actuation, forming the backbone of most existing UAV navigation architectures.

### 2.1 Hardware Architecture

The physical platform of an autonomous drone comprises several essential components that must work in harmony. The interaction between these components and the software stack is captured in the architectural diagram shown in **Figure 2**.

- i. **Frame and Propulsion System:** The airframe, typically constructed from lightweight composite materials like carbon fiber, houses the motors, propellers, and Electronic Speed Controllers (ESCs) that generate necessary thrust and maintain flight stability.
- ii. **Flight Controller:** This component acts as the central nervous system, executing low-level control algorithms that stabilize the drone through sophisticated sensor data fusion [9].
- iii. **Sensors:** Beyond visual sensors (monocular, stereo, or RGB-D cameras), drones incorporate Inertial Measurement Units (IMUs), GNSS receivers, barometers, and occasionally LiDAR or ultrasonic sensors. The IMU proves particularly crucial by providing high-frequency odometry data that complements and enhances vision-based estimation [10].
- iv. **Onboard Computing:** Embedded systems such as the NVIDIA Jetson series are commonly employed to execute the autonomy stack, offering a practical compromise between computational capability and energy efficiency [11].
- v. **Power System:** Lithium-polymer (Li-Po) batteries power all onboard electronics, though their limited energy density remains a primary constraint on operational endurance.

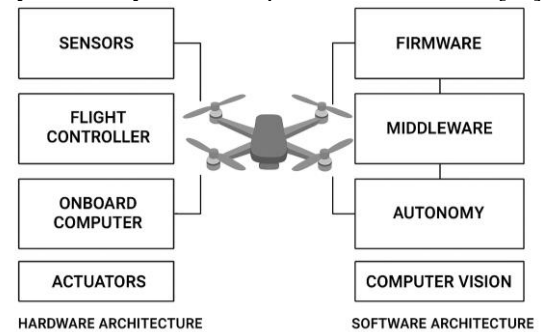
Significant hardware challenges persist, including limited battery life imposing strict operational time constraints, payload restrictions limiting sensor capabilities, sensor calibration drift affecting long-term accuracy, and vulnerability to environmental factors such as electromagnetic interference and temperature extremes [12].

### 2.2 Software Architecture

The software architecture follows a layered approach managing everything from low-level motor control to high-level intelligent decision-making, as visualized in the software block of **Figure-2**.

- i. **Firmware and Flight Stack:** Low-level software implementations (e.g., PX4 [9], ArduPilot) handle critical functions including sensor fusion, state estimation, and flight stabilization.
- ii. **Middleware:** Frameworks like the Robot Operating System (ROS) facilitate modular communication between software components, sensors, and actuators, promoting code reusability and system integration [13].
- iii. **Perception Stack:** This represents the core of the vision system, encompassing algorithms for object detection, semantic segmentation, Visual SLAM, and optical flow computation.
- iv. **Planning and Control:** This layer utilizes perceptual understanding to generate collision-free trajectories and executes them through the flight controller.

Persistent software challenges involve ensuring real-time performance guarantees, integrating heterogeneous sensors seamlessly, managing the substantial computational load of modern deep learning models, and guaranteeing system security and safety under all operational conditions [14].



**Figure 2:** A Typical Autonomous Drone Integrated Hardware and Software Architecture

To realize reliable autonomous operation, the integration of hardware and software components is crucial. **Figure-2** illustrates this interaction, depicting how sensors, onboard computers, flight controllers, and actuators cooperate through layered software frameworks. The hardware layer acquires and transmits multimodal data, while the software stack handles perception, decision-making, and control. This architecture highlights how seamless communication between physical components and computational modules enables real-time situational awareness and precise maneuver execution.

## 3. CORE COMPUTER VISION TECHNIQUES FOR DRONE NAVIGATION

The perceptual capabilities enabling autonomous drone operation build upon several foundational computer vision techniques, each addressing specific aspects of environmental understanding.

### 3.1 Object Detection and Recognition

Real-time object detection stands as a vital capability for obstacle avoidance and target tracking applications. Deep learning-based detectors including YOLO (You Only Look Once) [15] and SSD (Single Shot Multibox Detector) [16] have gained prominence due to their exceptional speed-accuracy trade-off, making them particularly suitable for UAV applications with limited computational resources. These models enable drones to identify and precisely localize objects such as vehicles, pedestrians, and infrastructure elements in real-time, forming the basis for reactive navigation behaviors.

### 3.2 Semantic Segmentation

For more granular environmental understanding, semantic segmentation provides pixel-wise classification of input images. Architectures like Fully Convolutional Networks (FCNs) [17] and DeepLab variants [18] allow drones to distinguish between navigable space, sky, buildings, vegetation, and other semantic categories. This detailed understanding proves crucial for safe navigation in complex, unstructured environments where simple obstacle detection proves insufficient for comprehensive scene interpretation.

### 3.3 Visual SLAM (V-SLAM) and Optical Flow

Visual SLAM enables drones to concurrently construct a map of unknown environments while estimating their position within this map. Feature-based methods exemplified by ORB-SLAM3 [19] have established benchmarks for accuracy and robustness. Direct methods, which utilize pixel intensity information directly, can offer superior efficiency in texture-rich environments [20]. Optical flow, representing the pattern of apparent motion of image objects between consecutive frames, finds application in velocity estimation, hover stabilization, and obstacle detection, proving especially valuable in GPS-denied scenarios [21].

### 3.4 Depth Estimation

Accurate depth perception remains critical for reliable obstacle avoidance and navigation safety. While stereo vision systems compute depth from disparity between two synchronized cameras, monocular depth estimation has gained significant traction due to lower hardware costs and reduced system complexity. Self-supervised learning approaches [22,23] have demonstrated remarkable effectiveness by learning to predict depth from monocular video sequences through photometric consistency constraints between frames, thereby circumventing the need for expensive ground-truth depth data collection.

## 4. DEEP LEARNING AI APPROACHES FOR AUTONOMOUS DRONE NAVIGATION

The perceptual capabilities enabling autonomous drone operation build upon several foundational computer vision techniques, each addressing specific aspects of environmental understanding.

### 4.1 CNN-based Navigation Models

Convolutional Neural Networks (CNNs) have served as the foundational workhorse for visual perception in drone systems. Their hierarchical architecture for spatial feature extraction from images makes them ideally suited for tasks including object detection [15], semantic segmentation [17], and terrain classification [24]. Furthermore, end-to-end CNN architectures have been explored that map raw visual input directly to control commands, effectively learning complete navigation policies [25]. For resource-constrained drones, lightweight architectures such as MobileNet [26] and EfficientNet [27] are frequently employed to maintain an

optimal balance between accuracy and computational efficiency.

### 4.2 Vision Transformers (ViTs)

Vision Transformers (ViTs) [28] represent a paradigm shift in visual processing, treating images as sequences of patches and employing self-attention mechanisms to model global context. This capability proves particularly beneficial for complex scene understanding in drone navigation, where comprehending relationships between distant objects (e.g., a path winding between trees or relationships between multiple obstacles) becomes critical for effective navigation. A comprehensive survey by Chen et al. [29] highlights the growing application of ViTs in robotics, noting their superior performance on tasks requiring holistic scene comprehension, though their substantial computational demands present challenges for real-time onboard deployment.

### 4.3 Reinforcement Learning for Path Planning

Reinforcement Learning (RL) provides a principled framework for drones to learn optimal navigation policies through trial and error interactions in simulated environments. Deep RL algorithms including Proximal Policy Optimization (PPO) [30] and Soft Actor-Critic (SAC) [31] can acquire complex behaviors such as mapless navigation in dynamic environments. The primary challenge involves the "sim-to-real" gap—successfully transferring policies learned in simulation to physical world operation without compromising safety or performance [32]. This domain continues to represent an active research area with significant practical implications.

### 4.4 Self-Supervised and Multi-Task Learning

To mitigate the substantial data annotation bottleneck inherent in supervised approaches, self-supervised learning (SSL) has emerged as a powerful alternative. By creating supervisory signals automatically from unlabeled data (e.g., using photometric consistency between video frames for depth estimation [22]), SSL dramatically reduces dependency on costly manual labeling. Multi-Task Learning (MTL) represents another promising direction, where a single model is trained to perform multiple related tasks concurrently (e.g., joint detection, segmentation, and depth estimation). MTL encourages learning of more robust, generalizable feature representations while improving computational efficiency [33], making it particularly attractive for UAV applications where computing resources must be shared across all perceptual tasks.

The evolution of perception pipelines has transitioned from traditional modular systems to integrated learning-based frameworks.

As shown in Figure~\ref{fig:learning\_arch}, the modular pipeline separates sensing, perception, estimation, and planning into discrete stages, allowing interpretability and ease of debugging but often accumulating error propagation across modules.

In contrast, end-to-end and multi-task learning architectures merge these functions within a unified deep neural network, enabling shared feature representations and potentially superior performance.

This comparison underscores a major paradigm shift toward learning-based autonomy, where system optimization focuses on joint perception-control performance rather than isolated module accuracy.

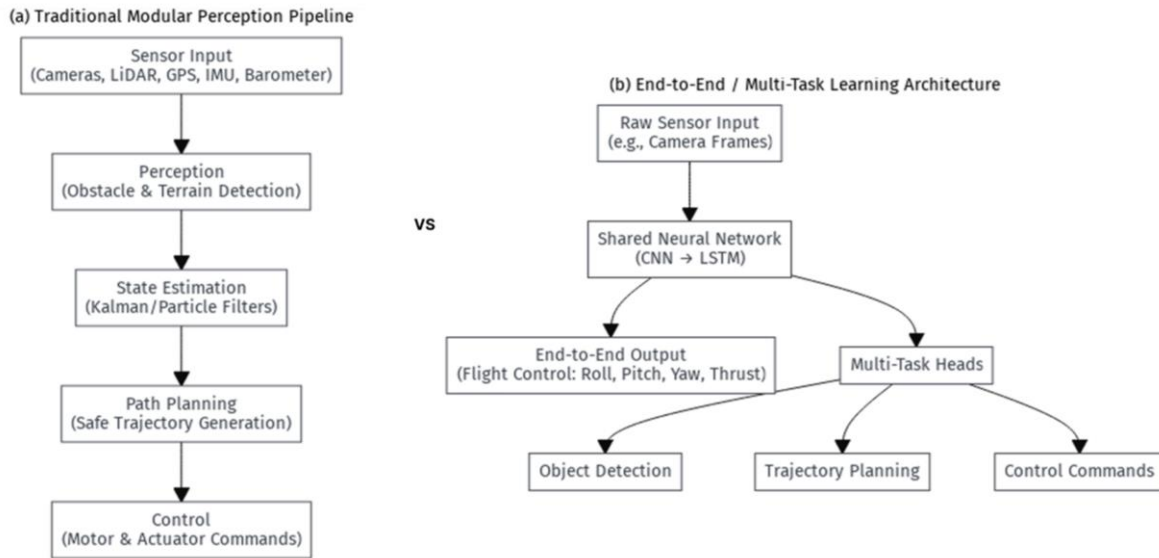


Figure 3: Traditional Modular Pipeline vs End-to-End Multi-Task Learning Architecture

## 5. KEY CHALLENGES IN VISION-BASED AUTONOMOUS NAVIGATION

Despite remarkable progress, several critical challenges continue to impede reliable deployment of vision-based autonomous drones in real-world scenarios, demanding continued research attention.

### 5.1 Robustness in Dynamic and Adverse Conditions

Visual perception systems exhibit high sensitivity to environmental variations. Changing lighting conditions (e.g., glare, shadows, rapid illumination changes), diverse weather phenomena (e.g., rain, fog, snow), and seasonal variations (e.g., foliage changes, snow cover) can dramatically degrade perceptual performance [6, 34]. For instance, fog induces light scattering that reduces image contrast and violates fundamental assumptions of many feature-based V-SLAM and object detection algorithms. Achieving all-weather, all-lighting robustness represents a primary unsolved problem in the field.

### 5.2 The Long-Tail Problem

Deep learning models are typically trained on large-scale datasets that inevitably underrepresent rare scenarios. Consequently, these models frequently demonstrate poor performance on "long-tail" events that occur infrequently during training but carry significant safety implications [8]. For autonomous drones, such events might include unusual obstacles (e.g., fallen trees on paths), atypical pedestrian behaviors, or specific architectural features not well-represented in training data. This lack of generalization to edge cases poses substantial safety risks for real-world deployment.

### 5.3 Real-Time Processing Under Computational Constraints

The fundamental conflict between the substantial computational demands of modern deep learning models and the limited power and processing capacity of UAV platforms creates a persistent bottleneck. Achieving low-latency inference for complex models like Vision Transformers or dense prediction networks on embedded hardware remains challenging [7], often forcing undesirable trade-offs between perceptual accuracy and operational feasibility.

### 5.4 Accurate Monocular Depth Estimation

While LiDAR provides precise depth information, its weight and power requirements often render it impractical for small drones. Monocular depth estimation offers a lightweight alternative but inherently lacks scale information and can demonstrate unreliability in textureless regions or under motion blur conditions [23]. Improving the accuracy and robustness of monocular depth prediction, particularly at longer ranges, continues as an active research area with significant practical implications.

### 5.5 Domain Shift and Sim-to-Real Transfer

Models trained in specific environments (or in simulation) frequently experience substantial performance degradation when deployed in different, unseen environments due to domain shift [35]. Similarly, policies learned in simulation often fail to transfer effectively to real-world operation. Developing robust domain adaptation and sim-to-real transfer techniques remains crucial for reducing the cost and complexity of real-world data collection and training procedures.

### 5.6 Security and Adversarial Attacks

Vision-based drones demonstrate vulnerability to adversarial attacks where malicious actors introduce subtle perturbations to the physical environment (e.g., carefully modified patterns on surfaces) that cause perception models to make critical errors [36]. Ensuring security and resilience of vision systems against such attacks represents a pressing concern for safety-critical applications where failure could have severe consequences.

Despite notable advances, several real-world challenges hinder robust autonomous navigation. Figure-4 visually summarizes three of the most critical limitations: (a) adverse weather and poor visibility, (b) long-tail or rare obstacle scenarios, and (c) limited onboard computational resources. Panel (a) demonstrates how fog, rain, or variable lighting degrade perception accuracy; panel (b) shows rare or unseen objects that disrupt model generalization; and panel (c) highlights the resource trade-offs in running deep models on lightweight hardware.

These challenges collectively emphasize the need for adaptive algorithms, efficient model design, and multimodal sensing to ensure dependable performance in unconstrained conditions.

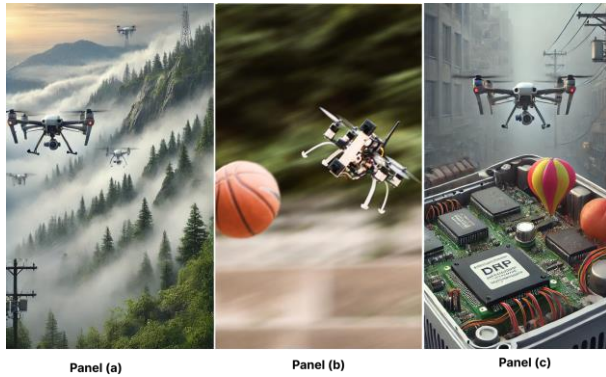


Figure 5: Challenges

## 6. CURRENT SOLUTIONS AND INNOVATIONS

The research community has developed various innovative solutions addressing the challenges previously outlined, representing significant advances toward practical vision-based navigation.

### 6.1 Advanced Architectures for Robust Perception

Hybrid architectures combining the computational efficiency of CNNs with the global context modeling capabilities of Transformers are being actively developed to achieve superior accuracy-efficiency trade-offs [37]. Furthermore, architectures specifically designed for robustness, incorporating attention mechanisms that dynamically focus on relevant features in adverse conditions, are demonstrating promising results [34]. These approaches enable more effective processing under challenging environmental conditions.

### 6.2 Enhanced Depth Estimation and Sensor Fusion

Recent monocular depth estimation methods including AdaBins [38] and LeReS [39] have achieved significant accuracy improvements through novel binning strategies and scale-invariant loss formulations. For maximum robustness, multi-modal sensor fusion frameworks combining cameras with lightweight LiDAR or high-frequency IMUs are being developed. Deep learning-based fusion methods can learn to optimally weight contributions from different sensors in real-time [40], adapting to changing environmental conditions and sensor reliability.

### 6.3 Domain Adaptation and Generalization Techniques

To combat domain shift, techniques including domain adversarial training [35] and style transfer [41] align feature distributions across different domains (e.g., simulation versus reality, or sunny versus rainy conditions). These methods enhance model generalization to unseen environments without requiring extensive labeled data from target domains, significantly reducing deployment barriers.

### 6.4 Data-Efficient and Self-Supervised Learning

Self-supervised learning for pre-training and fine-tuning is becoming standard practice to overcome data scarcity limitations [22,23]. Few-shot learning and meta-learning approaches are also being explored to enable models to rapidly adapt to new tasks or environments with minimal additional data [42]. These methodologies substantially reduce the data collection burden while improving model adaptability.

### 6.5 Model Optimization for Edge Deployment

Significant research effort focuses on making complex models suitable for edge deployment. Techniques including neural network pruning, quantization, and knowledge distillation effectively compress large models without substantial performance degradation [43]. The development of hardware-aware neural architecture search (NAS) produces models inherently efficient on specific embedded

platforms, optimizing performance within strict computational constraints.

### 6.6 Adversarial Robustness

To defend against adversarial attacks, strategies such as adversarial training [36]—where models are explicitly trained on adversarially perturbed examples—and input purification methods are being developed. System redundancy through sensor cross-checking (e.g., verifying vision-based decisions with inertial measurement data) further enhances overall system security against malicious interventions.

Recent research has proposed several strategies to overcome the challenges in vision-based drone navigation. As summarized in **Table-1**, recent studies address these limitations through a combination of domain adaptation, efficient network architectures, model compression, synthetic data generation, and robust training strategies. These approaches collectively aim to improve generalization, reduce computational cost, and enhance robustness under varying environmental conditions.

Table 1: Challenges and Solutions

Challenge	Current Solution
Robustness in Adverse Weather	Domain adaptation, robust architectures (ViTs), image enhancement techniques
Long-Tail Generalization	Data augmentation, few-shot learning, synthetic data generation
Computational Constraints	Model compression (pruning, quantization), efficient architectures (MobileViT)
Monocular Depth Estimation	Self-supervised learning, adaptive binning (AdaBins), scale-invariant losses (LeReS)
Domain Shift	Domain adversarial training, style transfer, simulation-to-real transfer learning
Adversarial Attacks	Adversarial training, input purification, multi-sensor cross-verification

As observed, most solutions emphasize data-centric and efficiency-oriented approaches. However, the integration of these methods into real-world UAV systems remains an open research direction, especially under dynamic and uncertain environments.

## 7. FUTURE DIRECTIONS AND OPEN RESEARCH PROBLEMS

Research in autonomous drone navigation is progressing toward several critical areas requiring further investigation to achieve robust, real-world deployment capabilities.

### 7.1 Unified and Explainable Perception Architectures

Future systems should transcend isolated perception modules toward unified, multi-task architectures that jointly perform detection, segmentation, depth estimation, and tracking. This integrated approach promotes feature sharing, reduces computational overhead, and can yield more consistent scene interpretation [44]. Concurrently, a growing imperative exists for explainable AI (XAI) in this safety-critical domain.

Developing methods that provide transparent, interpretable rationales for navigation decisions will prove crucial for system debugging, establishing user trust, and meeting regulatory requirements [45].

### 7.2 Neuromorphic Computing and Event-Based Vision

To overcome limitations of standard frame-based cameras and von Neumann computing architectures, future research should explore neuromorphic engineering approaches. Event-based cameras, outputting asynchronous pixel-level brightness changes, offer extremely high dynamic range and minimal motion blur, making them ideal for high-speed navigation in challenging lighting conditions [46]. Pairing these sensors with spiking neural networks (SNNs) on neuromorphic hardware could enable orders-of-magnitude improvements in energy efficiency and reaction times.

### 7.3 Federated and Continual Learning

Addressing the long-tail problem necessitates learning from operational data encountered during deployment. Federated learning frameworks would enable drone fleets to collaboratively learn from collective experiences without sharing raw, potentially sensitive data [47]. Combined with continual learning algorithms that allow models to acquire new tasks or adapt to new environments without catastrophic forgetting of previous knowledge, drones could become increasingly competent and specialized throughout their operational lifetimes.

### 7.4 Advanced Multi-Agent Collaborative Perception

The next frontier for drone autonomy involves collaborative operation. Enabling drones to share perceptual understanding in real-time via Vehicle-to-Everything (V2X) communication can create collective "scene graphs" surpassing the perspective of any single agent [48]. This capability proves vital for complex tasks including large-area search and rescue or coordinated warehouse logistics. Key research challenges include developing secure, low-latency communication protocols and robust data fusion algorithms for heterogeneous multi-agent data streams.

### 7.5 Physics-Informed and World Model-Based Learning

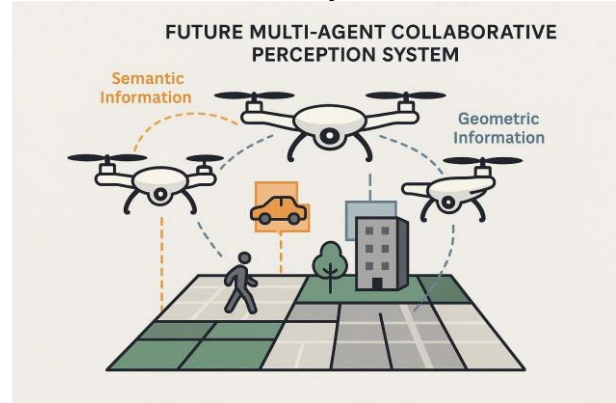
Integrating physical constraints and dynamics directly into learning models can enhance their plausibility and generalization capabilities. Future work should focus on developing "world models" that enable drones to predict action consequences and plan in learned latent spaces [49]. This approach appears particularly promising for sim-to-real transfer, as learning underlying environment physics typically transfers more effectively than learning pixel-level details susceptible to domain shifts.

### 7.6 Benchmarking and Standardized Testing

The research community would benefit significantly from more comprehensive benchmarking datasets and testing protocols explicitly focusing on long-tail scenarios and adverse weather conditions. Standardized virtual and physical testing environments, analogous to CARLA [50] for autonomous vehicles but tailored for aerial robotics, would accelerate progress and enable fair comparisons between different navigation systems.

Emerging research envisions collaborative perception as a pathway toward next-generation UAV intelligence. As depicted in **Figure-6**, multiple drones share both semantic and geometric information to construct a unified, comprehensive environmental map. This cooperation mitigates individual sensing limitations, enhances situational awareness, and enables collective decision-making in complex environments. The concept illustrates how distributed intelligence and inter-drone communication can

improve robustness, coverage, and safety—key enablers for scalable, swarm-based autonomy in real-world missions.



**Figure 6:** Future Multi-Agent Collaborative Perception System

This collaborative framework, illustrated in **Figure-6**, allows individual drones to overcome occlusions and limited field-of-view by fusing information from multiple perspectives, significantly enhancing overall situational awareness for the entire swarm.

## 8. CONCLUSION

This comprehensive review has examined the state-of-the-art in autonomous drone navigation using computer vision. We have traversed the foundational hardware and software architectures, detailed core computer vision techniques enabling environmental perception, and explored the transformative impact of deep learning models including CNNs, Vision Transformers, and Reinforcement Learning. A critical analysis identified enduring challenges, with particular emphasis on robustness in long-tail scenarios and adverse weather conditions—areas that continue to represent significant barriers to reliable deployment.

The survey of current solutions reveals a vibrant research landscape where innovations in model architecture, self-supervised learning, sensor fusion, and domain adaptation are steadily advancing performance boundaries. However, as outlined in future directions, achieving autonomy levels that are safe, efficient, and trustworthy in open-world environments requires concerted effort toward more unified, explainable, and adaptive systems. The integration of novel sensing paradigms like event-based vision, coupled with collaborative and continual learning frameworks, presents a promising path forward. The journey toward truly intelligent and resilient autonomous drones continues, with computer vision remaining the keystone technology in this endeavor.

## 9. ACKNOWLEDGEMENT

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