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Detection and Tracking of Drones Using Deep Learning and Computer Vision – A Survey

Dr P.K. Sharma[1], Mr. Manvendra Singh Divakar[2], Bharti Sahu[3]
[1]Principal, [2]Assistant Professor
[3]Research Scholar
[1,2,3]NRI Institute of Research & Technology, Bhopal (M.P.)

Abstract
The rapid expansion in the use of unmanned aerial vehicles (UAVs), commonly known as drones, has introduced serious challenges related to airspace security, public safety, and privacy. Unauthorized drone intrusions into sensitive zones such as airports, military installations, and critical infrastructure have necessitated the development of reliable and automated detection systems. Traditional drone detection approaches based on radar, acoustic sensing, or radio frequency analysis are often constrained by high cost, environmental sensitivity, and limited discrimination capability, particularly when dealing with small and low-altitude drones. In response to these limitations, deep learning–based computer vision techniques have emerged as a cost-effective and scalable alternative. This review paper critically examines a convolutional neural network (CNN)–based framework for drone detection and tracking using visual data. The reviewed system employs supervised deep learning to automatically learn discriminative visual features from drone and non-drone images, integrates detection with tracking to exploit temporal continuity, and evaluates performance using standard classification metrics. Experimental findings demonstrate an overall classification accuracy of 89.20%, with balanced precision, recall, and F1-score values for both drone and non-drone classes. Confusion matrix analysis confirms strong class separation with relatively low false positives and false negatives, while training–validation curves indicate stable convergence and good generalization. This review highlights the effectiveness, practical relevance, and limitations of deep learning–based computer vision approaches for intelligent drone surveillance systems.

Keywords: Drone Detection, Drone Tracking, Deep Learning, Computer Vision, Convolutional Neural Network, UAV Surveillance.

1. Introduction
The rapid proliferation of unmanned aerial vehicles (UAVs), commonly referred to as drones, has fundamentally reshaped the structure and dynamics of modern airspace. Over the past decade, drones have transitioned from niche military tools to widely accessible platforms deployed across civilian, commercial, and governmental sectors. Their affordability, maneuverability, and technological sophistication have enabled diverse applications, including aerial photography and videography, precision agriculture, infrastructure inspection, disaster response, logistics, environmental monitoring, and surveillance. These capabilities have delivered significant economic and societal benefits, improving efficiency, accessibility, and situational awareness across multiple domains. However, alongside these advantages, the widespread availability and ease of operation of drones have introduced serious challenges related to airspace security, public safety, and privacy protection. Unauthorized and malicious drone activities have become an increasingly prominent concern worldwide.
Numerous incidents involving drones operating near airports, government buildings, military installations, and critical infrastructure have underscored the potential risks posed by uncontrolled UAV operations. Such intrusions can disrupt airport operations, threaten passenger safety, facilitate espionage, or enable illicit activities such as smuggling and surveillance. In sensitive environments, even a small, low-cost drone can pose a disproportionate threat due to its ability to evade traditional monitoring systems and operate at low altitudes. These realities have created an urgent demand for reliable, automated, and scalable drone detection and tracking systems capable of operating continuously in complex real-world environments. Historically, drone detection

has relied on traditional sensing-based approaches, including radar, acoustic sensors, and radio frequency (RF) analysis. Radar systems, while effective for detecting large aircraft, often struggle to reliably identify small drones due to their low radar cross-sections and the presence of clutter in urban environments. Acoustic-based methods exploit the distinctive sound signatures generated by drone propellers, but their performance is highly sensitive to environmental noise, weather conditions, and distance. RF-based techniques aim to detect communication links between drones and their controllers; however, they are ineffective against autonomous drones or systems employing encrypted or non-standard communication protocols. Collectively, these approaches are often associated with high deployment and maintenance costs, limited scalability, and constrained discrimination capability, particularly when distinguishing drones from other airborne objects.

In this context, computer vision has emerged as a promising alternative for drone detection and tracking. Vision-based systems leverage widely available camera infrastructure and analyze visual information to identify drones based on appearance, shape, and motion characteristics. Compared to traditional sensing modalities, camera-based solutions are relatively cost-effective, flexible, and easier to integrate into existing surveillance networks. However, early vision-based drone detection approaches relied heavily on classical image processing techniques and handcrafted features, such as edge detection, motion segmentation, and contour analysis. While these methods demonstrated limited success in controlled settings, their performance degraded significantly in real-world scenarios characterized by cluttered backgrounds, varying illumination, dynamic weather conditions, and visual similarities between drones and other objects such as birds or debris.

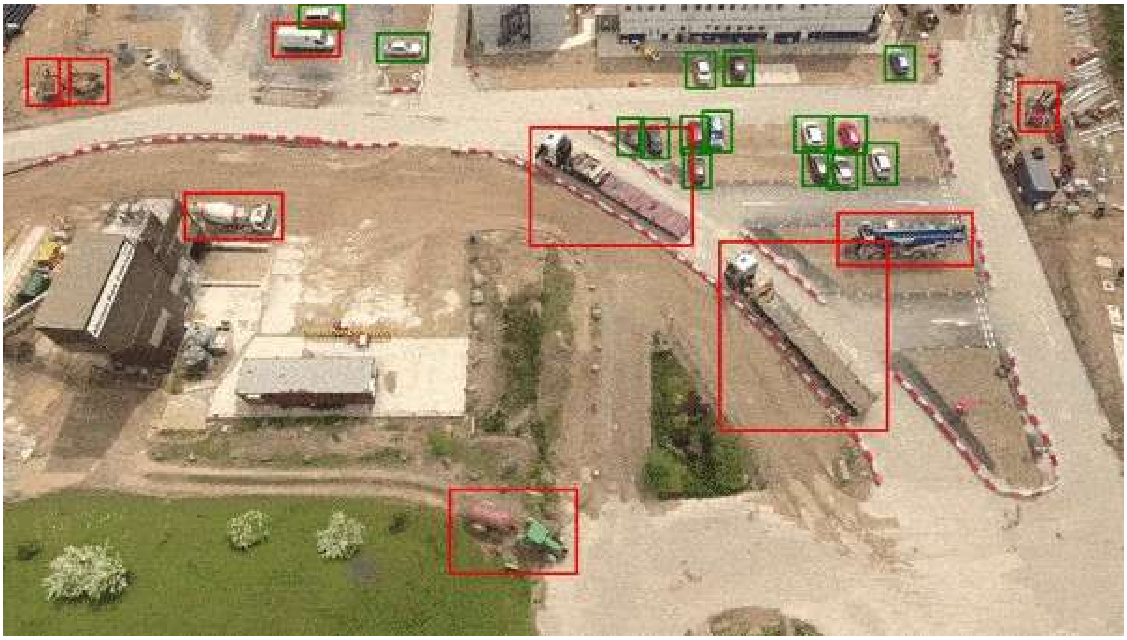

Figure 1.1: Visual representation of drone presence in restricted airspace and surveillance-based monitoring environments.

The integration of deep learning with computer vision has marked a significant turning point in drone detection research. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated exceptional capability in automatically learning hierarchical and discriminative visual features directly from raw image data. Unlike traditional approaches, CNN-based models eliminate the need for manual feature engineering and are better suited to handling the variability and complexity inherent in real-world visual environments. Through layered feature extraction, CNNs can capture both low-level visual cues, such as edges and textures, and high-level semantic patterns related to drone structure and geometry. This ability is especially critical for drone detection tasks, where targets are often small, fast-moving, and visually subtle. The reviewed dissertation positions deep learning–based computer vision as a robust and scalable solution to the challenges of drone detection and tracking. By combining CNN-driven detection with tracking mechanisms that exploit temporal continuity across video frames, the proposed framework aims to improve detection stability, reduce false alarms, and support continuous monitoring. This review synthesizes the dissertation's contributions by critically examining its methodological design, dataset preparation, model architecture, experimental evaluation, and reported results. Furthermore, the discussion situates these contributions within the broader research landscape of drone detection and tracking, highlighting both the strengths of the proposed approach and the persistent challenges that motivate ongoing research in intelligent aerial surveillance systems.

2. Role of Deep Learning in Vision-Based Drone Detection

Deep learning has emerged as a transformative paradigm in the field of computer vision, fundamentally reshaping how object detection and classification problems are approached. Its primary strength lies in the ability to automatically learn hierarchical feature representations from large-scale visual data, enabling models to capture complex and abstract patterns that are difficult to define manually. In the context of vision-based drone detection, this capability is especially valuable, as drones exhibit high variability in appearance, size, and motion, and often operate in visually challenging environments. The reviewed dissertation highlights convolutional neural networks (CNNs) as the central mechanism for addressing these challenges, positioning them as the core computational engine for reliable drone detection. Convolutional neural networks are particularly well suited to drone detection tasks because of their capacity to learn discriminative visual features directly from raw image inputs. Unlike traditional computer vision techniques that depend on handcrafted features such as edges, contours, or motion heuristics, CNNs learn feature hierarchies in a data-driven manner. Early convolutional layers typically extract low-level features such as edges, gradients, and textures, which are essential for identifying object boundaries. As data propagate through deeper layers, the network learns increasingly abstract and high-level representations, capturing structural and semantic characteristics that distinguish drones from non-drone objects such as birds, aircraft, clouds, and background elements. This hierarchical learning process enables CNNs to perform robust classification even when drones appear in complex visual scenes. The dissertation emphasizes that deep learning–based feature learning is particularly critical for drone detection because drones often appear as small, low-contrast objects occupying only a limited number of pixels within an image or video frame. Traditional vision-based methods struggle under these conditions, as handcrafted features tend to be sensitive to noise, background clutter, and illumination changes. CNN-based feature extraction, by contrast, demonstrates greater resilience to such variability. By learning multi-scale representations, CNNs can accommodate variations in drone size, orientation, and viewing angle, as well as changes in lighting and environmental conditions. This adaptability significantly enhances detection reliability in real-world surveillance scenarios. Another important contribution of deep learning highlighted in the reviewed work is its scalability and suitability for real-time processing. Once trained, CNN-based models can process large volumes of visual data efficiently, enabling continuous monitoring across multiple camera feeds. This capability is essential for modern surveillance systems, which often require uninterrupted operation with minimal human intervention. Furthermore, deep learning models can be optimized for deployment on resource-constrained platforms, supporting both centralized and distributed surveillance architectures. Beyond frame-level detection, the reviewed framework extends the role of deep learning by integrating detection with tracking mechanisms that exploit temporal continuity across video frames. By combining CNN-based detection with tracking, the system maintains object identity over time, reduces sporadic false detections, and improves overall detection stability. This integration demonstrates that deep learning not only enhances visual feature extraction but also plays a crucial role in enabling robust, end-to-end drone detection and tracking systems suitable for real-world applications.

3. Dataset, Preprocessing, and Model Architecture

The effectiveness of any deep learning–based vision system is fundamentally dependent on the quality of the dataset, the robustness of preprocessing techniques, and the suitability of the model architecture. In the reviewed work, a supervised learning approach is adopted using a carefully constructed and balanced visual dataset designed to support reliable drone detection. The dataset consists of a total of 4,000 images, evenly distributed between two classes: drone images and non-drone images, with 2,000 samples in each category. This balanced class distribution is an important design consideration, as it prevents bias toward a majority class and ensures that the model learns to discriminate equally between drone and non-drone objects. The non-drone category intentionally includes visually similar objects such as birds, aircraft, clouds, buildings, and other background elements, thereby increasing the difficulty of the classification task and encouraging the model to learn subtle and meaningful visual distinctions. Prior to model training, comprehensive preprocessing steps are applied to the dataset to enhance input quality and improve learning stability. All images are resized to uniform dimensions to ensure consistency in input representation and to enable efficient batch processing during training. Pixel value normalization is applied to scale image intensities to a standard range, which improves numerical stability and accelerates convergence during optimization. Noise reduction techniques are employed to minimize the impact of sensor noise and compression artifacts, which are common in real-world surveillance imagery. These preprocessing steps collectively ensure that irrelevant variations are suppressed while essential visual features associated with drone structures are preserved.

To further improve robustness and generalization capability, data augmentation techniques are incorporated into the preprocessing pipeline. Augmentation operations such as rotation, horizontal flipping, zooming, and brightness variation artificially expand the diversity of the training data without increasing dataset size. This strategy helps the model become invariant to changes in orientation, scale, and illumination, which are frequently encountered in real-world drone surveillance scenarios. By exposing the model to a broader range of visual variations during training, data augmentation effectively reduces the risk of overfitting and enhances performance on unseen data. The convolutional neural network architecture employed in the reviewed system is designed to strike a balance between detection accuracy and computational efficiency. The model contains approximately 314,561 trainable parameters, making it relatively lightweight compared to deeper and more complex architectures. This design choice is particularly important for real-time or near-real-time deployment in surveillance systems. The architecture comprises two convolutional layers with 32 and 64 filters, respectively, responsible for extracting low-level and mid-level visual features. Each convolutional layer is followed by a max pooling layer, which reduces spatial dimensions, improves translation invariance, and lowers computational complexity. Following feature extraction, a flatten layer converts the spatial feature maps into a one-dimensional representation, which is then processed by a fully connected dense layer with 128 neurons. Dropout regularization is applied at this stage to mitigate overfitting by randomly deactivating neurons during training. The final output layer consists of a single neuron with a sigmoid activation function, enabling binary classification between drone and non-drone classes. The network is trained using the Adam optimizer with a learning rate of 0.001, binary cross-entropy loss, a batch size of 32, and 10 training epochs, with a 20% validation split. This configuration ensures stable convergence, efficient learning, and reliable generalization performance.

4. Performance Evaluation and Experimental Results

A comprehensive and systematic performance evaluation is essential for assessing the reliability and practical applicability of any drone detection system, particularly in security- and surveillance-oriented contexts where misclassifications can have serious consequences. In the reviewed work, the performance of the proposed deep learning–based drone detection framework is evaluated using a combination of standard and widely accepted classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. Together, these metrics provide a holistic understanding of both overall system effectiveness and class-wise predictive behavior. The experimental results demonstrate that the proposed convolutional neural network achieves an overall classification accuracy of 89.20%. This level of accuracy is notable given the inherent challenges associated with vision-based drone detection, such as small object size, complex and cluttered backgrounds, and visual similarity between drones and other airborne objects. Accuracy serves as an initial indicator of model performance; however, in surveillance applications, it must be interpreted alongside more detailed metrics to fully understand system reliability.

For the non-drone class, the model achieves a precision of 0.8881, a recall of 0.8970, and an F1-score of 0.8925, evaluated over 1,000 test samples. The high recall value indicates that the system correctly identifies the majority of non-drone instances, thereby reducing the likelihood of falsely flagging benign objects as drones. This characteristic is particularly important in real-world deployments, where excessive false alarms can undermine operator trust and increase operational costs. The strong precision value further confirms that most non-drone predictions are accurate, reflecting effective background discrimination. For the drone class, the model records a precision of 0.8960, a recall of 0.8870, and an F1-score of 0.8915, also evaluated on 1,000 samples. High precision in drone detection signifies that when the system predicts the presence of a drone, it is highly likely to be correct, which is critical in security-sensitive environments such as airports and military installations. The recall value demonstrates that the majority of actual drone instances are successfully detected, indicating strong sensitivity to drone presence. The balanced F1-score confirms that the model maintains an effective trade-off between minimizing false alarms and avoiding missed detections.

Confusion matrix analysis provides deeper insight into the nature and distribution of classification errors. The model correctly classifies 897 non-drone samples and 887 drone samples, demonstrating strong diagonal dominance and clear class separation. The presence of 103 false positives suggests that certain non-drone objects, particularly those with visual characteristics similar to drones, may occasionally be misclassified. Conversely, the 113 false negatives indicate instances where drones were not detected, often due to factors such as low contrast, partial occlusion, or long-distance visibility. Importantly, the relatively balanced distribution of false positives and false negatives indicates that the model does not exhibit class bias and performs consistently across both categories. Further evidence of model reliability is provided by the training and validation accuracy and loss curves. Training accuracy shows a steady improvement from approximately 78% in the initial epoch to nearly 92% in the final epoch, reflecting effective learning of discriminative features. Validation accuracy closely follows this trend, reaching approximately 90%, with no significant divergence between training and validation curves. Validation loss stabilizes near 0.25, confirming stable convergence, effective regularization, and minimal overfitting. Collectively, these results demonstrate that the proposed model exhibits strong generalization capability and dependable performance suitable for real-world drone surveillance applications.

Table 1. Performance Summary of the Reviewed Drone Detection Model

Metric	**Non-Drone**	**Drone**	**Overall**
Precision	0.8881	0.8960	—
Recall	0.8970	0.8870	—
F1-Score	0.8925	0.8915	—

Correct Predictions	897	887	—
Overall Accuracy	—	—	**89.20%**

5. Integration of Detection and Tracking

While frame-level detection provides the fundamental capability to identify the presence of drones in individual images, effective surveillance systems require continuous monitoring to ensure reliable situational awareness. The reviewed framework addresses this requirement by integrating detection with tracking, thereby extending the system's functionality beyond isolated predictions to sustained observation over time. This integration represents a critical advancement in vision-based drone surveillance, as it allows the system to exploit temporal information inherent in video data and significantly enhances overall reliability. The detection-based tracking strategy employed in the reviewed system relies on the principle of temporal consistency. Once a drone is detected in an initial frame using the convolutional neural network, subsequent frames are analyzed to associate new detections with previously identified objects. This association is achieved through centroid tracking and bounding box overlap analysis, which compare the spatial proximity and geometric similarity of detected objects across consecutive frames. By evaluating whether detected regions correspond to the same physical object over time, the system maintains object identity and constructs a continuous representation of drone movement.

This tracking mechanism enables continuous monitoring of drone trajectories, which is essential for practical surveillance and security applications. By following a drone across multiple frames, the system can estimate motion-related parameters such as direction, speed, and persistence within the monitored airspace. These motion cues provide valuable contextual information that supports higher-level threat assessment and decision-making. For instance, sustained movement toward restricted zones may indicate malicious intent, while brief or erratic appearances may be associated with benign or transient objects. A key advantage of integrating detection with tracking is the reduction of sporadic false detections. In frame-based detection systems, visual noise, lighting fluctuations, or background artifacts may occasionally trigger false positives. However, such transient detections often lack temporal continuity and fail to reappear consistently across frames. The reviewed framework leverages this observation by discarding detections that do not persist over time, thereby enhancing confidence in genuine drone presence. This temporal filtering mechanism significantly improves system precision without substantially compromising recall.

The integration of detection and tracking also improves robustness under challenging visual conditions. Scenarios involving motion blur, partial occlusion, or rapid drone movement can temporarily degrade detection confidence in individual frames. Tracking compensates for these limitations by maintaining object identity based on prior detections, allowing the system to bridge short-term detection gaps. As a result, the system exhibits greater stability and reduced flickering in detection output, which is crucial for real-time surveillance environments. Furthermore, the detection–tracking integration supports real-time operation by employing computationally efficient tracking techniques. Centroid tracking and bounding box overlap analysis impose minimal computational overhead, making them well suited for deployment in continuous monitoring systems. Overall, the reviewed framework demonstrates that combining deep learning–based detection with computer vision–based tracking yields a more robust, reliable, and operationally effective drone surveillance system capable of supporting real-world security applications.

6. Discussion and Critical Insights

The reviewed dissertation provides compelling evidence that deep learning–based computer vision constitutes a robust, scalable, and practically viable solution for drone detection and tracking in modern surveillance environments. The reported experimental outcomes, particularly the overall classification accuracy of 89.20% combined with balanced precision and recall values across both drone and non-drone classes, clearly demonstrate the effectiveness of the proposed convolutional neural network architecture. These results indicate that the model is capable of learning discriminative visual representations that successfully separate drones from visually similar airborne objects, even in the presence of background clutter and environmental variability. From an operational perspective, such balanced performance is especially important, as it minimizes both false alarms and missed detections, which are critical factors in security-sensitive deployments. A notable strength of the reviewed framework lies in its lightweight architectural design. With approximately 314,561 trainable parameters, the model achieves a favorable balance between representational capacity and computational efficiency. This design choice directly supports the feasibility of real-time or near-real-time deployment, a key requirement for practical surveillance systems operating continuously over extended periods. Unlike highly complex deep learning models that demand extensive computational resources, the reviewed CNN architecture demonstrates that competitive performance can be achieved without excessive model depth or parameter count. This insight is particularly valuable for deployments on edge devices, smart cameras, or distributed surveillance networks where processing power and energy consumption are constrained. Despite these strengths, the discussion of results also reveals inherent limitations associated with vision-based drone detection. One of the most significant challenges highlighted by the experimental analysis is the occurrence of false negatives, where actual drone instances are not detected by the system. In security-critical applications, such missed detections pose a greater risk than false positives, as they may allow unauthorized drones to operate undetected in restricted airspace. The reviewed work attributes these errors primarily to factors such as extreme viewing distances, low contrast between drones and background elements, partial occlusion, and adverse environmental conditions. These challenges are intrinsic to visual sensing and underscore the difficulty of reliably detecting small objects in unconstrained outdoor environments. The discussion further suggests that while the proposed framework performs well within its defined scope, additional enhancements are necessary to improve robustness under extreme and adverse conditions. Future research directions may include the adoption of more advanced deep learning architectures capable of improved multi-scale feature representation, which could enhance sensitivity to small and distant drones. Similarly, incorporating complementary sensing modalities, such as radar or acoustic data, through multimodal fusion could mitigate some of the limitations of purely vision-based systems. Such approaches may improve detection reliability in scenarios where visual information alone is insufficient. Importantly, the reviewed framework establishes a strong and credible baseline for future advancements in drone surveillance research. By demonstrating that a relatively simple and efficient CNN-based system can achieve high accuracy and stable generalization, the dissertation provides a foundation upon which more sophisticated models, adaptive learning strategies, and optimized deployment solutions can be developed. Overall, the discussion highlights both the practical significance and the research potential of deep learning–driven computer vision systems for intelligent, real-world drone detection and tracking applications.

7. Conclusion

This review paper has presented a comprehensive and critical examination of a deep learning–based framework for drone detection and tracking using computer vision, as articulated in the reviewed dissertation. By systematically synthesizing the research methodology, dataset design, preprocessing strategies, convolutional neural network architecture, performance evaluation, and integration of detection with tracking, the review underscores the technical rigor and practical relevance of the proposed approach. The analysis demonstrates that deep learning–driven computer vision techniques represent a viable and effective solution to the growing challenges associated with unauthorized drone activities in modern airspace. One of the most significant contributions highlighted in this review is the effective use of convolutional neural networks for automated feature extraction in drone detection. The ability of CNNs to learn hierarchical visual representations directly from raw image data eliminates the reliance on handcrafted features, which have historically limited the robustness and generalization capability of traditional vision-based systems. The reported experimental results, particularly the overall classification accuracy of 89.20%, along with balanced precision, recall, and F1-score values for both drone and non-drone classes, provide strong empirical evidence of the model's effectiveness. Such balanced classification behavior is especially critical in security-sensitive surveillance applications, where both false alarms and missed detections can have serious operational consequences. The integration of detection with tracking further enhances the practical utility of the reviewed framework. By exploiting temporal continuity across video frames, the system improves detection stability, reduces sporadic false positives, and enables continuous monitoring of drone trajectories. This capability is essential for real-world surveillance environments, where reliable and persistent observation is required for threat assessment and response planning. The use of computationally efficient tracking mechanisms ensures that these benefits are achieved without imposing excessive processing overhead, supporting real-time or near-real-time deployment. Despite these strengths, the review also acknowledges the inherent limitations of vision-based drone detection systems. Challenges related to environmental variability, such as changes in lighting, weather conditions, background complexity, and camera motion, continue to affect detection reliability. Additionally, the problem of small object detection remains a significant concern, as drones operating at long distances or high altitudes may occupy only a few pixels within an image. These limitations indicate that, while the reviewed framework is robust and effective within its defined scope, further research is necessary to enhance performance under extreme and adverse conditions. Nevertheless, the reviewed work provides a strong and well-founded baseline for future research and development. It establishes that a relatively lightweight CNN architecture, when combined with appropriate preprocessing, training strategies, and tracking integration, can achieve competitive performance suitable for practical surveillance applications. Future extensions may build upon this foundation by incorporating more advanced deep learning architectures, multimodal sensing, adaptive learning strategies, and ethical considerations related to large-scale surveillance. In conclusion, this review affirms that deep learning–based computer vision frameworks hold substantial promise for the development of intelligent, scalable, and deployable drone monitoring systems capable of addressing contemporary airspace security challenges.

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