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Object Detection in Real-time Drone Surveillance using Deep Learning Algorithms: A Systematic Review, New Advancements, and Outstanding Questions

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***Abstract*:**

When it comes to analyzing photos taken by unmanned aerial vehicles (UAVs), deep learning (DL) has become an invaluable tool in the realm of remote sensing. Although it has made great strides in many fields, this review will shed light on the issue to help you understand it better. Included in the paper is a comprehensive review of current methods and their real-world uses for object recognition in drone surveillance in real-time.The following terms are associated with this article: unidentified aerial vehicles, deep learning, one-stage detector, two-stage detector.

I. INTRODUCTION

Drones, also known as Unmanned Aerial Vehicles (UAVs), have found several uses due to their capacity to reach inaccessible or hazardous locations that people would find difficult or impossible to reach on foot. Aerial photography, SAR operations, environmental monitoring, defense and military, and many more uses are possible with the cameras that UAVs have. These cameras can take still photographs or films from a variety of angles and heights. Due to the impossibility of manually monitoring and collecting these photos in real-time applications, automated systems that can handle and interpret UAV photographs are built using machine learning methods. However, picture capturing processes like mapping, surveying, inspection, and surveillance do not directly use it. Both real-time wireless transmission to a ground station and onboard storage of the photos for later retrieval and analysis are possible with UAVs. Figure 1 shows the fundamental design of the drone surveillance system. Drone surveillance usually makes use of an in-built camera on the aircraft to gather aerial footage. The application dictates the sort of sensor used by the camera; it might be a regular RGB camera or it could include thermal or multispectral sensors. The camera on board the drone takes pictures or videos of the ground below while it's in the air. The drone will either immediately send the footage or stills to a base station or save them for later use. The drone cameras might have their features and settings tweaked to provide the best possible images and to record certain kinds of data. The camera may, for instance, provide a variety of modes for taking still photos or video, as well as customizable settings for things like focus, zoom, and exposure. Along with the camera, the drone may also include other sensors and technologies like GPS and LIDAR that aid in navigating and mapping the area being monitored.

We will either keep the photographs in batches or monitor them in real-time from many places. Object detection is the procedure that allows us to track certain objects. The term "object detection" describes the steps used in drone surveillance to single out and pinpoint certain objects or characteristics in the recorded footage. Agriculture, environmental monitoring, SAR, and military activities are just a few of the many fields that have found drone surveillance to be an indispensable tool. Drones are a popular alternative for surveillance activities due to their capacity to effectively and swiftly deliver overhead images of broad regions. On the other hand, quick and accurate object identification algorithms are key to drone surveillance's efficacy. Due to the following factors, it is more difficult to detect drone surveillance than fixed cameras when these UAVs are flown at high altitudes: Looking down from above: shadows and reflections, as well as the challenge of correcting for perspective distortion, Unregulated setting: Factors that pose difficulties include environmental changes, illumination, and weather, things in motion: identifying and following

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things that could be traveling at great speeds or making sudden directional changes, Problems with processing power and memory mean that drone object identification algorithms can't be as sophisticated or accurate as they might be on a more powerful computer system.

II. OBJECT DETECTION UAV OVERVIEW

An Object: What Is It? An object is a graphically represented element that is taken from a UAV. To put it simply, object detection is the process of identifying and localizing objects—whether they be crops, flowers, people, weapons, etc.—in order to offer information about their position or status. A development of ML, Deep Learning (DL) is based on the hierarchical organization of the human brain and its ability to solve problems.

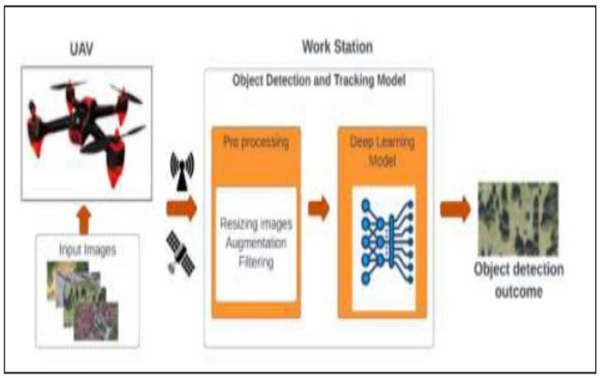

Figure 1 Sample Architecture for drone surveillance system

extensive and varied set of uses. Deep learning architectures are better at processing images and extracting features from complicated and big datasets because they use deeper combinations of input and hidden layers. Processing applications involving drones, which deal with data that is often varied and difficult to handle manually, benefit greatly from its high processing capabilities. This might be one explanation for the widespread use of DL in data-driven and image processing applications. Even if DL shows promise, a lot more testing and observation is still needed. It is worth noting that there were various object detection applications that utilized Hyperspectral Imaging Sensors (HIS) to take high-resolution images. These applications gained traction when it came to obtaining information about the physical and chemical properties of objects and terrain from these images (Petersson et al., 2017; Signoroni et al., 2019).

III. RESEARCH MOTIVATION

Computer vision, audio recognition, and natural language processing are just a few areas where deep learning techniques have shown great promise for object identification. In order to do object recognition tasks, deep learning algorithms may autonomously learn from massive datasets and extract pertinent information. This is why deep learning seems like a good strategy for drone object identification. There are several obstacles that must be overcome before deep learning can reach its full potential. These include issues with data quality, scarce computer resources, and the need for strong algorithms. Evaluating the existing state-of-the-art, identifying gaps in research, and proposing future research paths requires a study of object identification using deep learning in drone surveillance.

IV. RESEARCH CONTRIBUTION

This literature review aims to do just that by surveying the current research on object identification in drone surveillance applications of deep learning. The review will primarily contribute to the following areas: 1. In this study, we will take a look at how different deep learning algorithms and architectures handle object recognition, what their pros and cons are, and what problems and opportunities they may provide. 2. The purpose of this study is to provide light on the present state of the art and suggest avenues for future research that might enhance the efficacy of object detection in drone surveillance. 3. We want to make public drone datasets that include the relevant information in order to make further study in this field easier.

V. THE METHODOLOGICAL FRAMEWORK FOR LITERATURE REVIEW

The questions that guided the whole literature evaluation process were: Question 1: How have the most recent advanced object identification algorithms for drone surveillance, which are based on deep learning, changed over the years? The second question is, how can we get the most out of object identification algorithms that use deep learning for drone surveillance by tweaking their hyperparameters? Question 3: How can we enhance the effectiveness of object identification algorithms in drone surveillance that rely on deep learning by using transfer learning techniques? Question 4: How have researchers dealt with the difficulties of training object identification systems based on deep learning for use in drone surveillance? In addition, what are the necessary directions for the field to progress in

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the future? chapter six: answers to research questions Question 1: How have the most recent advanced object identification algorithms for drone surveillance, which are based on deep learning, changed over the years? Although object recognition often made use of older computer vision methods like Haar cascades and HOG (histogram of oriented gradients) before 2014. On the other hand, deep convolutional neural networks (CNNs) like AlexNet—which took first place in 2012's ImageNet Large Scale Visual Recognition Challenge—and other similar architectures began to replace traditional object recognition methods around 2014. Object recognition utilizing deep learning in drone surveillance was not yet commonplace, however there was definitely interest in employing drones for surveillance and other purposes around that time. Deep learning algorithms like YOLO, SSD, and Faster R-CNN didn't gain traction for object identification in UAV surveillance and other uses until much later. Since then, deep learning algorithms have seen substantial field applications (Figure 2). It was noted that R-CNN, Faster R-CNN, YOLO, and SSD are among the most popular deep learning algorithms in the object identification domain. All of these algorithms have shown to obtain top-tier results on object identification tasks by using CNNs as their foundation for feature extraction. Researchers are beginning to take an interest in other algorithms that were developed in early 2018, including CenterNet, Mask RCNN, M2Det, CPN, and FoveaBox. There are essentially three types of deep learning algorithms: one-stage, two-stage, and advanced detectors. a. Single-Process Detectors An example of an object detection approach in deep learning is the one-stage detector, which uses a single neural network pass to directly predict the bounding boxes and class probabilities of objects. Prior to identifying and honing down on a collection of potential objects, it suggests a number of zones of interest. A few well-known one-stage detectors include YOLO (You Only Look Once), SSD (Single Shot Detector), and RetinaNet (Redmon et al., 2016; Liu et al., 2016; Lin et al., 2020). For YOLO to function, the input picture is first divided into cells on a grid. Then, for each cell, the class probabilities and bounding boxes are predicted. A confidence score is assigned to each anticipated bounding box that indicates the likelihood that the box includes an item. b. Twin Detector Stages Due to their high accuracy and versatility, two-stage detectors are a strong family of object detection models. However, they may be computationally costly and are sensitive to the quality of candidate object suggestions. One of the most well-liked two-stage detector designs is the R-CNN family, which comprises the Fast, Faster, and Mask variants of the Region-based Convolutional Neural Network (R-CNN). In order to provide potential item suggestions, these models often use a Region Proposal Network (RPN), which is then classified by a second network. Some more well-known two-stage detectors include Hybrid Task Cascade, Cascade R-CNN, and Feature Pyramid Network (FPN). The two primary steps in the operation of a two-stage detector are the production of proposals and the categorization of results. As a first step, the model uses the input picture to create a list of potential objects to include in the final model. Usually, a neural network called a Region Proposal Network (RPN) is used for this purpose. It receives an image as input and produces a collection of bounding boxes that may include objects. In most cases, the RPN will generate an input picture feature map using a series of convolutional layers. After that, a tiny window is moved over the feature map and a set of predetermined anchor boxes are applied to each position to create a collection of possible object suggestions. Step two involves the model deciding whether each proposed item should be in the forefront (containing an object) or the background (non-containing an object). c. Detectors with Advanced Power. When compared to one-stage and two-stage detectors, advanced detectors perform better in terms of efficiency and accuracy, or both. Enhanced detectors include EfficientDet, CenterNet, YOLOv4, and DETR, to name a few. With a fraction of the parameters and processing required by earlier approaches, the EfficientDet family of object detectors developed by Google delivers state-of-the-art accuracy. To achieve the optimal balance between speed and accuracy, it employs a compound scaling method that adjusts the depth and size of the model. In contrast, YOLOv4 incorporates a new data augmentation approach called mosaic augmentation, uses anchor boxes with varied aspect ratios and sizes, and modifies the Darknet backbone network with additional layers. Table 1 displays a comprehensive comparison of the three detectors.

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Table 1. Comparison of different deep learning object detection techniques based on several performance constraints

Parameters	One Stage Detector	Two Stage Detector	Advanced Detector
Accuracy	Less	Medium	High
Speed	Faster	Slower	Faster
Model size	Smaller	Complex	Optimal
Data Volume	smaller datasets	Require large dataset	Versatile
Object size and shape	small objects	complex object shapes	multi-scale feature fusion
Training time	Less	Longer	Less

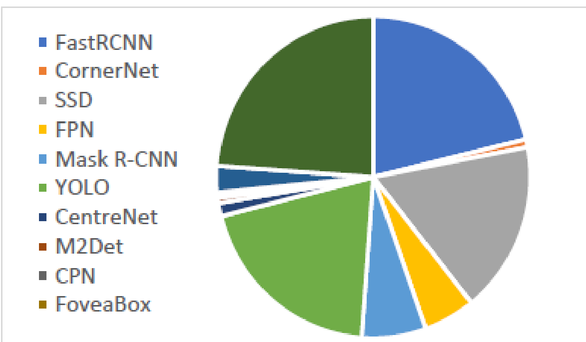

Figure 2 Relative percentage of different deep learning papers published in the UAV domain

The second question is, how can we get the most out of object identification algorithms that use deep learning for drone surveillance by tweaking their hyperparameters? Due to the time-consuming nature of training deep neural networks, optimization is an essential part of deep learning. Researches in various fields have developed optimizers for use with deep learning. Some examples include the stochastic gradient descent deep learning optimizer, the mini batch stochastic gradient descent optimizers, Adagrad, RMSProp, and others (Cui et al., 2018; Shallue et al., 2018; Zhang et al., 2019; Xu et al., 2021). There are a variety of methods for optimizing object identification models during runtime, including data augmentation, normalization, transfer learning, neural network learning rate adjustment, feature pyramid networks, and non-maximum suppression. Data augmentation is a regularization technique that involves enhancing the training data with controlled fluctuations. Overfitting occurs when a model becomes too dependent on its training data and is unable to generalize to new data. Regularization approaches are useful in avoiding this problem. Data augmentation improves the model's object detection accuracy on unseen data by supplying different instances, which in turn reduces overfitting and encourages the model to acquire more robust and generalizable features. In a 2014 study, Girshick et al. The research suggested a two-stage method for object identification utilizing the R-CNN framework. The first phase was to generate region recommendations. The second step was to categorize these proposals using a CNN. Although not directly stated as "data augmentation," the a2uthors used a method of data augmentation during training by randomly scaling and flipping the input pictures horizontally. The model's resilience and generalizability were both enhanced by this strategy. The use of data augmentation approaches during preprocessing has been reported in other studies to improve the object identification performance of DL models (Ottoni et al., 2023; Ruiz-Ponce et al., 2023) in a similar vein. Improving convergence is another way to optimize deep learning models (Zhang et al., 2019). In order to speed up the training of CNN models, batch normalization approaches were included into the model architecture by Ioffe and Szegedy (2015). These techniques acted as regularizers. With normalization, we were able to attain the same accuracy in only 14 fewer cycles, and we didn't even need to use dropout. A preprocessing strategy was suggested by Koo and Cha (2017) to improve the performance of an image recognition model. This technique applies normalization to a CNN classifier and feature extraction. In order to identify the normalized picture, a calibrated CaffeNet model is used. With the use of a size-normalized picture, the CNN model was able to improve its performance from an average of 93.24% to 96.85%. Another optimization strategy that has been useful for improving deep learning models in object identification is the transfer learning methodology (Aytar, 2014). Transfer learning does this by transferring learned information from one job to another, and it does this by making use of pretrained models on massive datasets.

In order to achieve the highest possible detection accuracy, the authors of (Chamarty, 2020) focused on optimizing CNN's learning rate. The paper achieved a relationship between learning rate and dataset size in the range of 10-4 to 10-5. A learning rate optimization method was used in (Na, 2022) to adjust the learning rate based on adjusting the direction of multipliers. When compared to existing adaptive gradient algorithms, the suggested strategies for modifying the learning rate performed better. Feature Pyramid Networks can efficiently deal with objects of varying sizes (Yang et al., 2022). Object identification, instance segmentation, semantic

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segmentation, and Non-Maximum Suppression are just a few of the tasks that may be enhanced using FPN's multiscale information pyramid, which allows for the detection and recognition of objects of different sizes (Song et al., 2019). Various optimization approaches used in the domain are detailed in Figure 3.

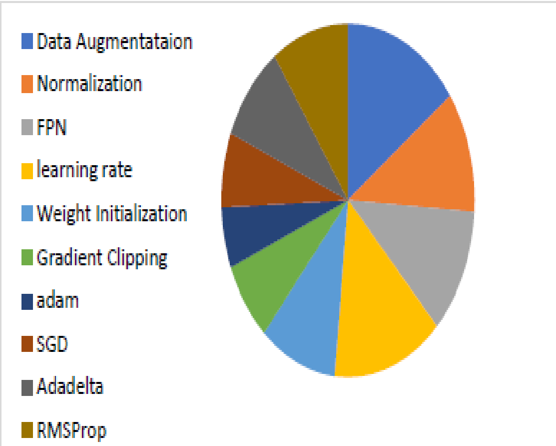

Figure 3 Count of each Optimization techniques applied on deep learning algorithm in various literatures towards object detection

Question 3: How can we enhance the effectiveness of object identification algorithms in drone surveillance that rely on deep learning by using transfer learning techniques? Drone surveillance systems that use deep learning for object identification may greatly benefit from transfer learning. Drone surveillance algorithms that use deep learning for object recognition might benefit from this method's ability to reduce computing resources, speed up training, and enhance performance. Here is one possible application of transfer learning to object recognition; Algorithm 1 lays out the process in great detail:

Algorithm 1: Step by step process of transfer learning for object detection

1. Select a pre trained model.
2. Choose the input data extracted through drone.
3. Transfer Learning Process
   - I. Load the pre-trained model and freeze the early layers
   - II. Use the pre-trained model as feature extractor
   - III. Training and fine tuning (Iterate through steps 3(i), (ii), (iii))
     - i. Train the modified model, update the weights for new layers, retain the knowledge gained from previous steps.
     - ii. Adjusting parameters such as learning rate, batch size, optimizer, and regularization techniques.
     - iii. Asses the performance based on precision, recall and f1 score.
   - iv. Fine-tuning the model or adjusting hyperparameters, include re-annotating data, collecting additional data, or experimenting with different model architectures.
4. Final Output (A fine-tuned or Adapted Model)

In order to train object identification algorithms for drone surveillance, what are the challenges? Several obstacles must be overcome in order to train object identification systems for drone surveillance that rely on deep learning: First, there is a lack of labeled data. It takes a lot of time and energy to collect and classify a dataset that includes all the possible situations, weather, illumination, and item changes that the drone may see. When labeled data is few, it might be difficult to train the model and make it more or less applicable to real-world scenarios.2. Changes in the domain: Traditional object identification datasets and drone surveillance frequently use different image circumstances. High altitude, changing views, occlusions, and motion blur are some of the particular issues that drones bring to aerial photography and videography. Due to domain shifts caused by these variations, pretrained models may not be able to generalize well to the domain of drone surveillance. In these novel settings, the model could need further training or fine-tuning to achieve successful item detection. Depending on the drone's height and distance from the objects of interest, drone surveillance often includes identifying things at varied sizes. This brings us to our third point, object scale and resolution. It might be somewhat tough for the model to recognize and locate objects effectively in scenes when their size varies significantly or when they look tiny. The resolution of drone cameras isn't always high enough to make fine details visible in the footage or stills. If you want accurate object identification results, you have to solve these problems with size and resolution. 4. Performance in real-time: In order to make quick decisions, drone surveillance applications often need object detection in real-time or near real-time. Since drones often have limited computing power, it might be difficult to implement deep learning-based object identification algorithms at the required speed. Optimization methods such as model compression, quantization, or hardware acceleration could be necessary to strike a balance between detection accuracy and real-time speed.5. Adjusting to ever-changing environments: Capturing images with moving objects and shifting backdrops is a common part of drone surveillance. Interesting things could be moving in complicated patterns, occluding other objects, or interacting with one another. An extensive dataset including different motion patterns and item interactions is necessary for training a model capable of properly handling such dynamic situations. Capturing the temporal information in drone surveillance films also requires careful model architecture design and temporal modeling approaches. 6. Drones' restricted flight duration is caused by their battery capacity, which in turn limits the quantity of data that can be acquired during each flying session. Because of this restriction, collecting a big enough and representative dataset is not an easy task. Data gathering may also be limited in certain places or under some situations due to rules, privacy concerns, or operational restrictions, which further limits the dataset's variety and quantity.

VII. CONCLUSION

Although there is continuous research to dispel the notion that deep learning (DL) is a "black-box" solution, many still see it as such. Deep learning (DL) has created substantial progress in remote sensing for a number of uses. The application of DL approaches to the analysis of photos taken by UAVs is the primary emphasis of our literature study. Our research presents an overview of state-of-the-art methodologies and viewpoints on their application with the intention of providing a full grasp of the issue. One goal of this literature review is to provide a comprehensive overview of the uses of DL-based methods for UAV image processing. It is determined from this review that: 1. While most published works on object recognition using deep learning focus on convolutional neural networks (CNNs) and radial basis functions (RCNNs), multi-and hyperspectral data might be useful in some applications, such as precision agriculture and forest-related tasks. 2. It is evident that more publicly accessible datasets specially collected by UAVs are needed to improve network training and benchmarking. In order for researchers to train and assess their networks efficiently, it is crucial that these datasets be appropriately labeled to support supervised learning methods. 3. By combining GPU processing with deep learning (DL) techniques, fast inference solutions may be provided, allowing for efficient and speedy data processing. Still, further investigation into UAV-specific embedded systems for real-time processing is required.

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