

YOLOv8 in a WSN Using UAV Aerial Photography

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Contributor: Shakila Rahman, Jahid Hasan Rony, Jia Uddin, Md Abdus Samad

Wireless sensor networks (WSNs) have a significant and long-lasting impact on numerous fields that affect all facets of our lives, including governmental, civil, and military applications. WSNs contain sensor nodes linked together via wireless communication links that need to relay data instantly or subsequently.

Keywords: YOLOv8 ; wireless sensor networks (WSNs) ; obstacle detection

1. Introduction

Unmanned aerial vehicles (UAVs) have become a ubiquitous part of our daily lives, with their applications ranging from aerial photography to military reconnaissance ^{[1][2]}. The term UAV, also known as a drone, refers to a flying vehicle that can be remotely controlled or operated autonomously. The versatility of drones has made them an essential tool for a wide range of industries, from agriculture ^[3] and construction to emergency services and national security. Drones' autonomy is one of their most important characteristics, especially for military and security purposes. Drones with autonomous piloting may be pre-programmed with precise flight paths and can fly without human control ^[4]. Since drones may be employed for reconnaissance and surveillance tasks in military and security operations, this function is very beneficial.

Another critical feature of drones, particularly for military and security purposes, is real-time object detection. Drones equipped with object detection technologies can identify and follow both stationary and moving objects in real-time ^[5]. Advanced sensors and cameras that drones may be fitted with allow them to instantly detect and monitor possible threats, giving military and security personnel vital knowledge in real time. For real-time object detection, cutting-edge machine learning techniques and computer vision technologies are employed. These algorithms enable drones to recognize and classify diverse things within their field of view based on patterns and characteristics discovered by their sensors and cameras. The algorithms may also be trained to identify new objects and improve their accuracy over time, making them better and better at recognizing and tracking objects in a range of situations.

However, there are a number of challenges associated with real-time object detection, particularly in the processing and interpretation of data. Drones generate a lot of data, including images, video recordings, and sensor readings, which must be instantly evaluated in order to successfully detect objects. This necessitates efficient infrastructure for data transmission and storage in addition to reliable processing hardware and software. Assuring the precision and dependability of object detection algorithms is another difficulty, particularly in complex and dynamic situations. For example, a drone flying in a crowded urban area may encounter a wide range of objects and obstacles, including buildings, trees, bikes, cars, pedestrians, animals, and other drones. The algorithms must be able to distinguish between different objects and accurately track their movements, even in challenging conditions such as poor lighting or inclement weather conditions. Despite these difficulties, real-time object identification is a critical capability of drones in a variety of applications, from aerial photography to military surveillance and beyond. Drones will probably become much more adaptable and efficient as technology develops over time, with the capacity to find and follow objects in surroundings that are more complicated and dynamic.

Alongside military and security applications, drones are also very useful for a wide range of commercial and civilian applications. For example, drones can be used for aerial photography and videography. This allows photographers and filmmakers to capture stunning images and footage from unique perspectives without risking human life ^[6]. Drones can also be used for mapping and surveying applications ^[7], allowing for the rapid and accurate collection of geographical data. In the agriculture industry, drones are increasingly being used for crop monitoring and management purposes. Drones equipped with advanced sensors and cameras can capture high-resolution images and data that can be used to detect crop stress, nutrient deficiencies, and other issues that can impact crop health and yield effects. This information can then be used to make data-driven decisions about the crop management sector, including irrigation, fertilization, and pest control. Drones are being utilized in emergency services for search and rescue operations, enabling rescuers to

swiftly find and reach people in distant or inaccessible places. Drones using thermal imaging cameras can also be used to find people who went missing or who are buried under rubble or other materials [8][9].

The study in [10] improved obstacle detection and collision avoidance in drones with weight constraints; the proposed method employs lightweight monocular cameras for depth computation. It extracts key point features using computer vision algorithms like Harris corner detector and SIFT, then matches them using Brute Force Matching (BFM) to detect increasing obstacle sizes as the drone approaches. Another paper [11] presented an indoor obstacle detection algorithm that combines YOLO with a light field camera, offering a simpler setup than RGB-D sensors. It accurately calculates obstacle size and position using object information and depth maps, demonstrating higher detection accuracy indoors.

Overall, drones are a versatile and useful tool for a wide range of applications, from military and security to commercial and civilian. Drones are projected to become increasingly important in the years to come, delivering valuable insights and information in a variety of businesses and fields because of their capacity to function independently and detect objects in real time. Drones will surely advance and be able to carry out a larger variety of jobs and applications as technology continues to advance. However, it is also important to ensure that drones are used ethically and responsibly, particularly in military and security applications, to prevent potential risks and negative consequences. With the right guidance and regulations, drones have the potential to revolutionize many different industries and provide numerous benefits to society. From these perspectives, researchers have shown here an advanced deep learning model to effectively detect both static and moving objects in real time from unmanned aerial vehicle data. In this case, the proposed scenario is a UAV-based wireless sensor network (WSN) system where multiple UAVs collect data from a group of sensors while avoiding all obstacles in their traveling path and where the obstacles are detected based on the UAVs' captured photography.

2. YOLOv8 in a WSN Using UAV Aerial Photography

UAVs are currently a trending topic in the research world, with numerous studies and projects exploring their potential applications and capabilities. Using the drone camera feature to detect and classify objects is one of the most important and useful features of UAVs. Different kinds of traditional machine learning, deep learning, as well as transfer learning models have been applied and tested. For example, in [12], the authors propose three algorithms that combine an object detector and visual tracker for single-object detection and tracking in videos, using limited training data based on the convolutional neural network (CNN) model. The algorithms efficiently incorporate the temporal and contextual information of the target object by switching between the detector and tracker or using them in combination. Another study has used the TensorFlow object detection API to implement object detection on drone videos and compare the performance of different target detection algorithms [13]. CNNs with transfer learning are used to recognize objects such as buildings, cars, trees, and people. The study shows that the choice of target detection algorithm affects detection accuracy and performance consumption in different ways. Hybrid models have also shown promises; for example, [14] proposed a method for vehicle detection in UAV videos using a combination of optical flow, connected graph theory, and CNN-SVM algorithms, which achieved 98% accuracy in detecting vehicles in moving videos. However, those traditional models are computationally expensive and require a lot of processing power.

Apart from these, various lightweight models such as MobileNet, SSD, and YOLO have gathered attention for object detection using drones. Widodo et al. discussed the development of object detection using deep learning for drone-based medical aid delivery, using a combination of Single Shot Detector (SSD) and the MobileNet framework to efficiently detect and locate objects in video streams [15]. Then, a real-time drone detection algorithm based on modified YOLOv3 with improvements in network structure and multi-scale detection achieved 95.60% accuracy and 96% average precision in detecting small drone objects [16]. A paper [17] applied the YOLOv3 algorithm for robust obstacle detection. It introduced the YOLOv3 network structure, multi-scale target detection principles, and implementation steps. Experimental results demonstrated improved robustness compared to YOLOv2, with increased detection in complex backgrounds, better lighting, low illumination contrast, and even in poor lighting conditions. YOLOv3 outperforms YOLOv2 by accurately detecting small, distant targets, such as pedestrians, in front of the track. After that, the newer version, YOLOv4, was introduced, and different studies found better accuracy and speed using this version [18]. A further improved YOLOv4 model was proposed for small object detection in surveillance drones, achieving 2% better mean average precision (mAP) results on the VisDrone dataset while maintaining the same speed as the original YOLOv4 [19]. A study [20] proposed a real-time obstacle detection method for coal mine environments, addressing low illumination, motion blur, and other challenges. It combined DeblurGANv2 for image deblurring, a modified YOLOv4 with MobileNetv2 for faster detection, and SANet attention modules for better accuracy. Experimental results showed significant improvements in detection performance. However, YOLOv5 is one of the most popular methods. As an example, a study achieved high recall and mAP scores on a combined dataset from a challenge and a publicly available UAV dataset [21]. The model leverages PANet neck and mosaic augmentation to improve the detection of small objects in complex background and lighting

conditions. Some other papers proposed an improvised version of the YOLOv5 model for object detection and compared its performance to the original YOLOv5 model [22][23]. Another study proposed a YOLOv5-like architecture with ConvMixers and an additional prediction head for object detection using UAVs, which were trained and tested on the VisDrone 2021 dataset. Furthermore, the authors in [24] modified the YOLOv5 architecture for better aerial image analysis performance, concentrating on uses like mapping land usage and environmental monitoring.

Then, YOLOv6, a newer version with faster inference and accuracy, came into play. A study evaluated YOLOv6 for fire detection in Korea, showing high performance and real-time capabilities [25]. XGBoost achieved the highest accuracy for object identification. Data augmentation and Efficient Net improved YOLOv6's performance. However, limitations included smoke classification and accuracy in poorly illuminated environments. Another piece of research suggested a transfer learning-based model using YOLOv6 for real-time object detection in embedded environments [26]. Pruning and finetuning algorithms improve accuracy and speed. The model identifies objects and provides voice output. It outperforms other models, is simple to set up, and has the potential for assisting visually impaired individuals in an IoT environment. But the model faces difficulty identifying objects against textured backgrounds and potential challenges in compressing network width.

Still, the YOLOv6 model requires a large dataset and is computationally expensive. Thus, recently, YOLOv7 was introduced, producing a higher mAP on the COCO dataset than YOLOv6, using the EfficientRep backbone and SimOTA training. It is also faster and more efficient at using GPU hardware. A few studies have been conducted to perform object detection using YOLOv7 [27][28][29]. The authors in [27] used an improved YOLOv7-based object detection method designed specifically for marine unmanned aerial vehicle (UAV) photos. In [28], the proposed YOLOv7-UAV algorithm performs UAV-based object detection tasks with better accuracy, making it appropriate for use in remote sensing, agriculture, and surveillance. The improvements improve detection accuracy by altering the anchor box aspect ratios and using multi-scale training techniques. The study in [29] supports sustainable agricultural practices and presents YOLOv7 as a useful tool for automated weed detection and crop management. But, as a complex model, YOLOv7 has scope to improve accuracy and reduce noise sensitivity. Furthermore, the work in [30] was optimized for aerial photography taken by unmanned aerial vehicles (UAVs), wherein multi-scale characteristics were added to YOLOv7 to improve object detection precision in UAV photos. This is why, most recently, YOLOv8 has been revealed.

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