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MULTIPLE FLYING OBJECT DETECTION USING MACHINE LEARNING ALGORITHM

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ABSTRACT

Detecting multiple flying objects is a crucial task in various domains such as surveillance, wildlife monitoring, and airspace management. This paper presents an approach to detect multiple flying objects using object detection algorithms. The process involves several key steps, including data collection and annotation, preprocessing, model selection, training, evaluation, deployment, real-time detection, post-processing, and monitoring. Initially, a diverse dataset containing images or videos with various flying objects is gathered, and annotations are added to label each object with its corresponding class and bounding box coordinates. Preprocessing techniques like resizing, normalization, and augmentation are applied to enhance the dataset. Next, a suitable object detection algorithm is selected, considering factors like performance and computational efficiency. Common choices include YOLO model, depending on the specific requirements of the application. The chosen model is trained using the annotated dataset, fine-tuned, and evaluated using metrics like precision, recall, and mean Average Precision (mAP). Upon satisfactory performance, the model is deployed in the desired environment, integrated with appropriate hardware for real-time detection. Post-processing techniques such as non-maximum suppression (NMS) are applied to refine the detected bounding boxes, ensuring accurate identification of multiple flying objects. Regular monitoring and maintenance are conducted to keep the deployed model up-to-date and effective in dynamically changing environments.

Keywords: Multi Type Flying Object Detection, Machine Learning, Deep Learning, Object Detection, Object Recognition

1. INTRODUCTION

Target detection has attracted significant attention for autonomous aerial vehicles due to its notable benefits and recent progress. Target tracking with an unmanned aerial vehicle (UAV) of guidance systems. Pedestrian detection, dynamic vehicle detection, and obstacle detection can improve the features of the guiding assistance system. Object recognition technologies for self- driving vehicles have strict requirements in terms of accuracy, unambiguousness, robustness, space demand, and costs. Similarly, object recognition and tracking features in an aerial vehicle can assist in drone navigation and obstacle avoidance. Visual recognition systems in a UAV can be used in many applications, like video surveillance, self- driving systems [6], a panoramic aerial view for traffic management, traffic surveillance, road conditions, and emergency response, which has been the interest of transportation departments for many years. The process of flying object detection involves taking the moving objects out of a video clip. Many techniques, including edge detection, frame differencing, background subtraction, and the optical flow method, have been presented. One popular technique for separating foreground elements from background in a video sequence is background removal. It is computed by taking the current frame and subtracting it from the "background image," or reference frame. Its performance is always reliant on how well the backdrop modelling is done. This method's ease of implementation and quick, precise detection are its main advantages. With a moving camera, it is inapplicable since the background of every frame will change. By computing the difference between the current frame and the preceding frame in a video sequence, a technique known as frame differencing is used to extract moving objects. The frame difference algorithm's benefits include ease of implementation and excellent adaptability to dynamic scene changes. low computing complexity in comparison. Despite its benefits, this method is not always effective in extracting all relevant pixels from moving regions because it cannot locate large interior pixels with uniformly distributed intensity values. One popular technique for detecting things is the optical flow method. calculation. By analysing changes in the image's intensity values, the edge detection method transforms the original images into edge images. Based on characteristics such as edge, curve, and straight line, the edges are recovered from the video and thus allows for object detection. Figure 1 shows drone detection setup.

2. RELATED WORK

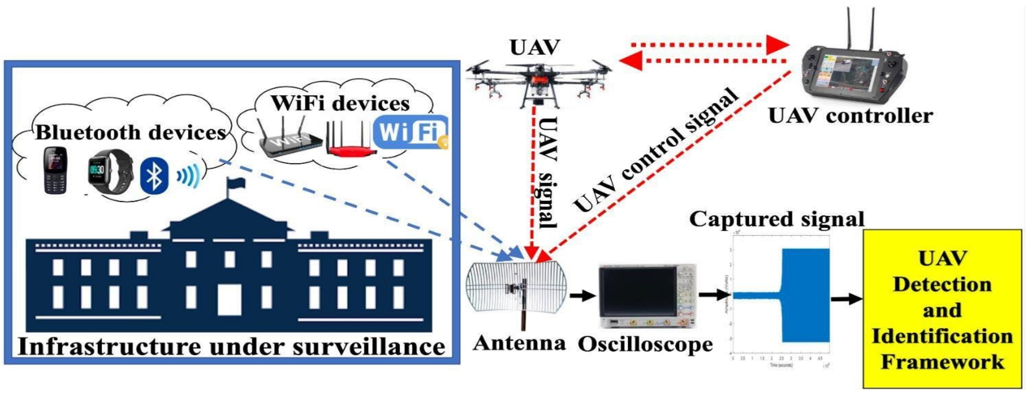

Fig 1: Drone detection setup

as classes alongside birds to improve the model's

Burchan Aydin, et.al,…[1] compared the performance of one of the latest versions of YOLO, YOLOv5, to our previously proposed drone detection methodology that used YOLOv4. To make a fair comparison, we employed the same dataset and the same computing configurations (e.g., GPU). We first fine-tuned the original YOLOv5, as per our customized dataset that had two classes: bird and drone. We further tuned the values of the hyperparameters (e.g., learning rate, momentum, and decay) to improve the detection accuracy. In order to speed up the training, we used transfer learning, implementing the pre- trained weights provided with the original YOLOv5. The weights were trained on a popular and commonly used dataset called MS COCO. To address data scarcity and overfitting issues, we used data augmentation via Roboflow API and included data preprocessing techniques to smoothly train the model. To evaluate the model's performance, we calculated the evaluation metrics on a testing dataset. We used precision, recall, F- 1 score, and mAP, achieving 0.918, 0.875, 0.896, and 0.904 values, respectively. The videos were taken at three altitudes—20 ft, 40 ft, and 60ft—to test the capability of the detector for objects at high altitudes. In future work, we will use different versions of YOLO and larger datasets. In addition, other algorithms for object detection will be included to compare the performance. Various drone-like objects such as airplanes will be added ability to distinguish among similar objects.-

Driss Aouladhadj, et.al,…[2] the conducted study provides insight into drone detection and tracking systems, focusing particularly on the Mavic Air, Mavic 3, and Mavic 2 Pro drones. The research outlines the detection range for these drones, with maximum detected distances at 1.3 km, 1.5 km, and 3.7 km, respectively. The detection capabilities are influenced by factors such as the drone's transmission power and multipath propagation, contributing to the variation in the observed results. The research notes an increase in position estimation error as drones move further away from the system. The relative error in estimating speed and altitude also increased with distance, though these did not exceed 7% and 14%, respectively. The use of the Haversine equation in estimating the remaining distance between the detected drone and the system yielded promising results. The system was also tested in a hypothetical scenario involving securing an area with a 200 m radius. The remaining reaction times for different drones were computed, providing useful data for applications aiming at the interception of unauthorized drones.

Misha Urooj Khan, et.al,…[3] propose a precise and efficient multi-feature and multi-scale UAV detection network, i.e., SafeSpace MultiFeatureNet (MFNet). We address the pre- discussed gaps by developing an open dataset and proposing a real-time detection model which can excellently classify birds vs. UAVs with speedy inference time via attention given to the most important feature maps. And proposed the novel SafeSpace MultifeatureNet (MFNet) architecture that significantly improved the precision and mAP in UAV detection compared to YOLOv5s. To successfully implement the proposed architecture and test its validity in challenging weather conditions, we gathered the existing five datasets of birds and UAVs from the literature to verify its performance on three MFNet/MFNet FA variants. All algorithms' detection performance was rigorously examined and analyzed with varying environmental backgrounds (i.e., weather conditions) and target scales. Proposed MFNet/MFNet-FA-small, MFNet/MFNet-FA- medium, and MFNet/MFNet-FA-large successfully detected and identified UAVs with the highest UAV detection precision compared to YOLOv5s and the existing state-of-the-art schemes.

Artem Rozantsev, et.al,…[4] detect whether an object of interest is present and constitutes a danger by classifying 3D descriptors computed from spatio-temporal image cubes. We will refer to them as st-cubes. These st-cubes are formed by stacking motion-stabilized image windows over several consecutive frames, which gives more information than using a single image. What makes this approach both practical and effective is a regression-based motion- stabilization algorithm. Unlike those that rely on optical flow, it remains effective even when the shape of the object to be detected is blurry or barely visible. And showed that temporal information from a sequence of frames plays a vital role in detection of small fast moving objects like UAVs or aircrafts in complex outdoor environments. We therefore developed an object-centric motion compensation approach that is robust to changes of the appearances of both the object and the background. This approach allows us to outperform state-of-the-art techniques on two challenging datasets. Motion information provided by our method has a variety of applications, from detection of potential collision situations to improvement of vision guided tracking algorithms.

Frederik S. Leira, et.al,…[5] proposed an automatic object detection, recognition, and tracking algorithm has been developed. The algorithm is intended to be used in an ocean surface object tracking system for UAVs, to enable UAVs to perform multi-object tracking and situational awareness in real time. The detection algorithm uses a combination of edge detection and thresholding, together with dilatation/eroding and finding connected components to perform real-time automatic object detection from a thermal camera's video stream. Using onboard navigation data to get the UAV's and camera's attitude and altitude, the onboard computer is able to geo-reference each object detection to measure the location of detected objects in a local NED coordinate frame. Furthermore, the tracking algorithm uses a Kalman filter and a constant velocity motion model to perform object tracking based on the position measurements found using the object detection algorithm. The object detection algorithm developed in this paper was found to consistently detect the objects of interest in a given thermal image. However, these detection results would of course not be expected if the UAVs were to fly over land (or a small island at sea), as the algorithm largely depends on the thermal signatures of objects to be located on a surface with a uniform emission of thermal radiation.

3. EXISTING METHODOLOGIES

Traditional radar systems, while effective in detecting larger aircraft, face challenges in detecting smaller and low-flying objects like drones due to their size and low radar cross- section. Furthermore, radar systems lack the capability to provide detailed information about the type and purpose of detected objects. Human surveillance, often aided by binoculars or optical tools, is a vital component in monitoring airspace, but it is constrained by limitations in coverage, response time, and continuous monitoring. This paper explores the limitations of radar systems and human surveillance in detecting smaller and low-flying objects, emphasizing the need for alternative solutions. Object detection algorithms, particularly those based on machine learning and computer vision, offer promising avenues for addressing these limitations by providing automated, detailed, and real-time detection of diverse flying objects. The integration of such algorithms with existing radar systems and surveillance infrastructure presents an opportunity to enhance airspace monitoring capabilities, enabling more comprehensive and effective detection of both large and small airborne threats. This paper discusses the potential of object detection algorithms as a complementary solution to radar systems and human surveillance in addressing the challenges posed by smaller and low-flying objects in airspace monitoring. Human surveillance, augmented by optical tools like binoculars, offers a complementary approach but suffers from inherent limitations. Coverage is restricted by human presence, response time can be delayed, and continuous monitoring becomes impractical over extended periods.

4. PROPOSED METHODOLOGIES

Real-time object detection remains challenging due to variances in object spatial sizes and aspect ratios, inference speed, and noise. This is especially true for our use case, as flying objects can change location, scale, rotation, and trajectory very quickly. This conveys the necessity for fast inference speed and thorough model evaluation between low-variance classes, object sizes, rotations, backgrounds, and aspect ratios. Computer vision in drones has gained a lot of attention from artificial intelligence researchers. Providing intelligence to drones will resolve many real-time problems. Computer vision tasks such as object detection, object tracking, and object counting are significant tasks for monitoring specified environments. However, factors such as altitude, camera angle, occlusion, and motion blur make it a more challenging task. Yolo implemented a new strategy to object detection. The feature extraction module and object localization module are combined into a unique monolithic entity. Besides, the heads of localization and classification are also combined. This single-stage architecture results in quick inference time. Together with the other detectors based on Convolutional neural network, this new strategy has brought the vision of edge devices ever close to existence. The concept behind YOLO is this: there are no separate classification or detection modules that should be synchronized with each other and no repeated region proposals as in region-based detectors. The unique monolithic network performs all tasks such as feature extraction, boundary box regression, and classification. It contains only one output layer with different features.

5. EXPERIMENTAL RESULTS

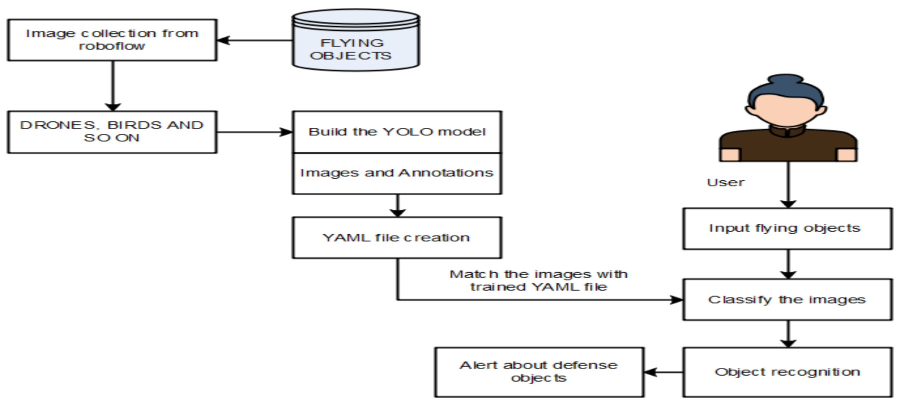

Fig 2: Proposed architecture

TRAINING ACCURACY

Number of Correct Predictions on Training set

In this simulation, we can collect the flying object datasets from Roboflow interface which contains the classes such as drones, birds, jets and so on. Training accuracy is a metric used in deep learning to evaluate how well a model performs on the training dataset during the training phase. It represents the percentage of correctly predicted instances out of the total instances in the training set.

The formula for training accuracy is: = Total number of instances in Training set X 100%

A high training accuracy indicates that the model has learned the patterns and features present in the training data well. However, a high training accuracy does not necessarily guarantee good performance on unseen or new data (i.e., the test set). Overfitting is a common concern when the training accuracy is significantly higher than the test accuracy. Overfitting occurs when the model learns the training data too closely, capturing noise and outliers that may not be representative of the overall dataset.

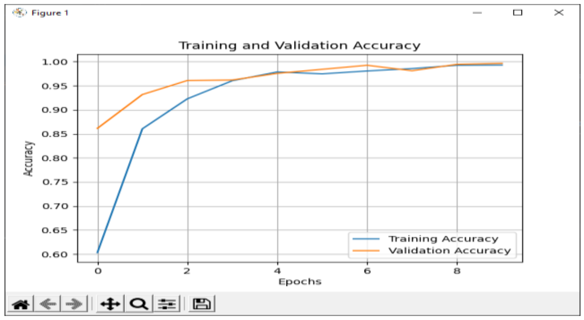

Fig 3: Training accuracy

The proposed system provides improved accuracy in flying objects detection.

6. CONCLUSION

In conclusion, the proposed system for multi-type flying objects detection utilizing the YOLO algorithm offers a promising solution to address the limitations of traditional radar systems and human surveillance methods. By leveraging the real-time object detection capabilities of YOLO, the system provides enhanced detection speed, accuracy, and detailed information about detected objects. Through the collection and annotation of diverse datasets, the YOLO algorithm is trained to detect various types of flying objects simultaneously. Once trained, the algorithm is deployed in a real-time detection module, capable of efficiently processing input from sensors such as cameras or drones. Post- processing techniques, including non-maximum suppression and data fusion, are employed to refine detections and integrate information from multiple sensors, further enhancing the system's detection capabilities. The proposed system offers several advantages, including improved situational awareness, timely threat detection, and effective response mechanisms. It finds applications in diverse fields such as aviation, border surveillance, and wildlife conservation, contributing to enhanced safety and security in airspace monitoring.

CONFLICT OF INTERESTS

None.

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