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Autonomous Obstacle Detection and Avoidance in Drones

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Abstract

Drone technology has recently advanced, and object detection technology is already evolving. These technologies can be used to find illegal immigrants, locate missing people and items, and detect industrial and natural disasters. In this research, we investigate how to improve object detection performance in such cases. Photography was carried out in a setting where it was difficult to identify objects. The experimental data was based on images taken under various situations, such as changing the drone's altitude, shooting pictures in the dark, and so on. In this work, we recommend a way to make YOLO models more effective at detecting objects. To determine the key indicators, we will input the collected data into the CNN model and the YOLO model, respectively. Precision, recall, F-1 score, and mAP are the major metrics of evaluation. On the basis of the data comparing the CNN model with the YOLO model, an inference will then be drawn.

Keywords: Autonomous Drones, Object Detection, Obstacle avoidance, Path Planning, Navigation, CNN, Yolo V4, Flight Control, Collision Avoidance, Sensor Integration, Safety Critical System, LiDAR, Airsim, Gazebo, Unreal Engine.

Introduction

Unmanned aerial vehicles (UAVs) are now used for non-military purposes due to advancements in microelectronics and increased processing efficiency during the past ten years. The demands of operations and applications at low altitudes have recently increased with the development of tiny and micro aerial vehicles (sUAVs and MAVs). sUAVs and MAVs, particularly helicopters and vertical take-off and landing (VTOL) rotor-craft systems, are being used more and more in a variety of applications, including surveying and mapping, disaster rescue operations, the acquisition of spatial information, the gathering of data from inaccessible locations, geophysics exploration, assisting in manipulation and transportation, inspecting buildings, and navigation. Drone technology has recently experienced significant growth, and it is anticipated that they will eventually be integrated into a variety of industries

to produce high value. Particularly, low-cost drone photography technology can support the local economy or assist researchers in studying culturally significant coastal areas. In this paper, we investigate how drone photography can improve the performance of object detection models. Modern UAVs seek for increased levels of autonomy and flight stabilisation due to the state of technology, the variety, and the complexity of the jobs. The ability of autonomous UAVs to detect and avoid obstacles with a high degree of accuracy is seen as a tough topic. The challenge arises because UAVs are becoming smaller and lighter as a result of this trend. Because of these characteristics, sUAVs and MAVs are unable to transport bulky sensors like laser or radar. Thus, using on-board cameras is the best option due to

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their advantages of being lightweight and using less power. The cameras offer rich environmental data in addition to being lightweight and using little electricity. They are regarded as crucial sensors put on small and micro-UAVs as a result. Several strategies were put forth in vision-based navigation systems to address the issue of obstacle identification and avoidance.

Drones are frequently used to look for objects at accident or catastrophe sites. However, it might be challenging to find missing people or items when vision is compromised by snow and rain. Drones are also used in areas like automatic licence plate recognition, diseased plant detection, traffic signal detection for autonomous vehicles, and ship detection in SAR images. Drone-based object detection has been studied and developed as a solution to the subject issue, but the body of knowledge in this area is rather limited. In addition to the instances listed above, it can be employed in a wide range of other situations as well. The use of drones for object detection will advance and become more prevalent in the future. This paper addresses how to distinguish items in a complicated environment and detect them well in order to address these issues. Convolutional layers are the primary layers of YOLO, allows us to effectively increase the model's performance. In this study, we show how mAP (0.5) and loss function interact with activation function.

Literature Review

[1] The problem of 2D object detection from images is that it is as old as computer vision. Furthermore, it has to Detect the object, classify the object, categorize the object and also recognize the object.

They suggested a system that categorises object recognition techniques according to the flying height and application domain that are registered at various heights. R-CNN, a two-stage object detector that uses selective search to look for potential object locations, was utilised for this.

For this they used a public dataset containing labelled images. Since they are labelled, it was easy for the system to categorize the object thus helping it in easy object detection. For an unlabelled dataset this systems performance will be decreased. Therefore, non-heterogeneous data from various sensing devices will be used to advance this field of study.

[2] A deep learning system must be combined with a UAV in order to solve the problem of top-down view angles and compute-intensive procedures.

Their proposed system is in three methods / modules. First method, The research of this paper is to determine how existing object detection systems and models can be used on image data from a drone. they used convolution neural network as a fixed feature extractor. The second method involves fine-tuning CNNs, and it employs continuous back propagation to adjust the pre-trained network's weights. The final approach is to employ the many pre-trained models in the TensorFlow model zoo.

Because convolutional neural networks are computationally expensive, they employed the transfer learning method to train their neural network while making a compromise with the dataset size, i.e., they chose a smaller dataset. The average time is at least 140ms to detect the items in each frame.

[3] Object detection in images taken by unmanned aerial vehicles (UAVs) has long been a challenge in the field of computer vision. Specifically because people, buildings, water, hills, and other objects come in a variety of sizes, object detection in drone photographs is a difficult process.

In this paper, they explain the use of ensemble transfer learning to enhance the performance of the fundamental models for multiscale object detection in drone footage. When combined with a test-time augmentation pipeline, the technique recognises objects of varying scales in UAV photographs by combining many models and using voting strategies.

Due to their absence from the training datasets, they discovered limits in this methodology's ability to detect novel objects like awning tricycles and tricycles. Multiscale object detection can be used to create better-quality orthomosaics using the methodology described in this study for drone-

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based object detection, especially for objects present around the margins of the orthophoto.

[4] It is difficult to identify and categorize objects in a single frame that contains multiple objects. The accuracy rate has greatly increased as deep learning techniques have advanced.

This work provides a cutting-edge proprietary algorithm for object detection and classification in a single frame to achieve high accuracy with real-time performance. The suggested systems integrate MobileNet with SSD architecture for maximum accuracy. The system will be rapid enough to identify numerous objects even at 30 frames per second.

Many of the things in this research are challenging to properly recognise due to frame noise or poor video quality. The second limitation of this research is that the model for detection and classification was developed for low computational devices, which prevents the system from processing high quality video.

[5] In contrast to other recommended techniques like RADAR, acoustics, and RF signal analysis, computer vision is widely utilised to identify drones autonomously due to its robustness. Deep learning algorithms are favoured over other computer vision-based techniques because to their effectiveness.

A static wide-angle camera and a lower-angle camera mounted on a rotating turret are used in this research's autonomous drone identification and tracking system. In order to utilise both time and memory effectively, they introduced a combined multi-frame deep learning detection technique that overlays the wide-angle static camera's frame with the zoomed camera's frame. They have seen that small drones may be found even with this much thinner construction, but occasionally get false alarms. This element of the system should be used as a main filter for prospective targets because this method would not always detect only intended items.

[6] In order to preserve peace and avoid disruption, it is crucial to monitor and find unauthorized drones entering the restricted areas. Yolo is a powerful technique that has recently been employed for real-time object or image detection. In order to distinguish between them and avoid making incorrect predictions about drones, the Yolo trained model is trained using images of birds and drones.

The proposed system consists of three parts: real-time video recording utilising 360-degree CCTV; trained model for drone detection in the video. . Because of its real-time identification capabilities, fast speed, and accuracy, the YOLO-v4 algorithm has been chosen as the state-of-the-art in object detection for this investigation.

Because of their small size, high altitude, speed, and presence of drone-like objects, drones at different altitudes become difficult to identify. A previous version of YOLO is called v3. There are now versions 7 and 8 of YOLO.

[7] Multi-class object detection has advanced quickly in recent years with the emergence of deep convolutional neural networks (CNNs) based on learning. Drones are now more readily available, which has sparked the creation of many inventive uses. Analyzing, recognizing, and identifying numerous elements in the area are necessary to comprehend drone footage.

This study trains and evaluates the CNN networks that will be investigated using a series of enormous photographs that were shot by a drone flying at a fixed altitude in the United Arab Emirates (UAE) desert. Three cutting-edge CNN architectures have been optimally configured, retrained, tested, and evaluated for the detection of three different classes of objects in the captured footage: palm trees, herds of animals or cattle, and farm animal sheds: YOLO-V3 with Darknet-53, SSD-500 with VGGNet-16 meta-architecture, SSD-500 with ResNet meta-architecture, and SSD-500 with VGGNet-16 meta-architecture.

For multiclass detection, the research's F1-score for SSD-500/VGG-Net is 0.77, and for SSD-500/ResNet, it is 0.83. SSD-500 with VGG-16 registered the lowest F1-score and outperformed SSD-500 with ResNet, making the effect of the

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number of convolution layers clear. The YOLO-V3 design can outperform this since the detection phase comprises 53 convolutional layers rather than the SSD architecture's five.

[8] The topic of creating an intelligent UAV is one that is both interesting and difficult. Recent times have seen a significant increase in the usage of deep learning and computer vision to create completely autonomous drones. Convolutional neural networks are employed in the field of computer vision to help drones analyze and comprehend the content of images and videos (CNNs).
The main goal of this study is to analyze contemporary deep learning-based object identification algorithms for UAVs, including CNN, R-CNN, Fast R-CNN, YOLO, SSD, and others. We'll go over the most significant studies and methods that helped advance drone object detection technology.
In this study they used different methods to locate the accuracy they were getting are around 70-80 percent depending on the method they were using.

[9] The paper aims to provide a comprehensive analysis of recent advancements in object detection techniques based on deep learning, specifically in the context of low altitude UAV datasets. This focus is because there is relatively little information available in the literature on this topic compared to standard or remote-sensing datasets. The paper covers a range of algorithms, including Faster RCNN, Cascade RCNN, R-FCN, YOLO and its variations, SSD, RetinaNet, and CornerNet, Objects as Point, etc., with a particular emphasis on one, two, and advanced stages of detectors for low-altitude UAV datasets.

Despite the high resolution of low-altitude aerial photos, which are typically around 2,000 by 1,500 pixels, most images in conventional datasets such as MS-COCO have a resolution of less than 500 by 500 pixels. The paper also highlights the challenges of object detection in low-altitude aerial VisDrone datasets, where even the most advanced detector, CornerNet, achieves an average mAP of only 17.41, compared to the much higher 40.6 shown in Table VI.

[10] As it relates to our day-to-day struggles, the topic of safety and monitoring has been under discussion for a very long time. These problems are the result of rules and regulations being broken or ignored. Numerous regrettable events, including the loss of life, have been brought on by violations of safety regulations and traffic laws. In addition to this, there have also been cases of breaking traffic signals, emergency road situations, burglaries, shootings, and explosions.
The researchers aimed to develop a video surveillance system that integrates three stages of data processing: identifying moving objects, recognizing and tracking them, and making decisions about how to respond to events of interest. This involves several different tasks such as detecting and identifying anomalies, detecting objects, classifying and tracking moving vehicles for number plate recognition, and identifying safety gear such as helmets for drivers and safety vests and boots for workers on construction sites, among other aspects.
The background subtraction method produces inaccurate results and detects items with noise. Nothing is picked up that is behind the object. Every robotic mobility system has benefits and drawbacks, and Rover is no exception. Low ability to ascend quite steep slopes, which might lead to wheel slippage; Low ability to navigate obstacles in comparison to other concepts; Track friction; The Rover's slow functioning speed is one of its biggest drawbacks.

[11] The objective of this research was to develop a video surveillance system that incorporates drone technology, enabling the study of aerial view photos and videos without restrictions. While object detection algorithms created using ground-based photos have been successful, their performance decreases significantly when applied to images taken by unmanned aerial vehicles (UAVs). To address this issue, the researchers

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proposed a sample balancing strategies module to improve the imbalance between training samples, particularly positive and negative, and easy and hard samples. The detection of small objects in drone photos is challenging due to high frequencies and noisy representations, but their method outperformed previous algorithms. They also suggested a super-resolved generated GAN module with center-ness weights to improve the local feature map.

The datasets for object detection in drone scenarios are less comprehensive than those used in ground-based datasets like ImageNet, and detecting tiny objects is the primary focus. Therefore, research typically focuses on improving aspects such as loss design, training sample selection, and feature augmentation to enhance detector performance.

[12] Numerous issues have been resolved via object detection in a variety of applications, including autonomous driving, semantic segmentation, search and rescue operations, and security monitoring. Despite the enormous success rate in images taken from the ground, it can be difficult to identify people or other objects in UAV (unmanned aerial vehicle) images because of issues with pose and scale, weather, artefacts like hats worn by people, varying attitude, and environments that have been camouflaged.

In this study, they put out a brand-new method for spotting people in aerial photos for search and rescue operations. This technique describes how to train the current HERIDAL high-resolution aerial database. To address the human identification issue, the EfficientDET deep neural network is trained using a recently created database. The system utilised by Croatian Mountain SAR teams (IPSAR) and the cutting-edge proposed HERIDAL database study, both of which rely on extracting prominent features, have been compared to the proposed method. The results of the latter paper are marginally poorer than those of the former.

This wouldn't work properly in high altitudes such as hills. On open space these methods could find/identify the person but is closed environment or environment covered with more objects, it becomes difficult to identify the human.

[13] The goal is to develop a self-governing Unmanned Aerial Vehicle (UAV) that can navigate a trail independently while evading obstacles, by employing Deep Neural Networks. The UAV must remain close to the centre of the trail by utilizing Convolutional Neural Networks (CNN) for guidance. However, there may be instances where the UAV deviates from the trail due to external interferences or unfavourable weather, resulting in the camera failing to detect the trail.

[14] The goal is to precisely identify and monitor objects through camera-based technology on unmanned aerial vehicles (UAVs). A suggestion is made for an algorithm that employs deep learning to identify and track moving objects. However, it is difficult to maintain stability when dealing with rapidly changing backgrounds in non-flat environments for UAV usage.

[15] To use object detection and navigation systems to deliver important medical aids and supply packages for patients in emergency situations and make developments in the field of agriculture using the right technology.

To create a deep learning-based approach using GPS for navigation and object detection. The created model is to be fitted in a quadcopter drone. Gathering sufficient data in an outdoor setting that lacks a defined structure is difficult.

[16] Since the start of the Covid pandemic, there has been a significant rise in the utilization of delivery services. To provide faster and less expensive delivery services, there is a keen interest in creating drone delivery systems. The suggested system comprises a navigation system that utilizes GPS, 9DOF IMU, and a barometer to track its location and follow its designated path.

A crucial obstacle in drone delivery is achieving consistent and secure landings in urban locations.

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[17] Hardware systems are more susceptible to transient and persistent defects, which pose a serious threat to task safety.

In learning-based navigation systems, the research suggests two error mitigation strategies that increase success rates by double and flight quality by 39%.

Implementing conventional protection techniques that rely on redundancy is difficult to achieve on edge applications that have limited resources.

[18] The challenge of maneuvering a UAV in complex indoor or outdoor settings is difficult due to the greater range of possible movements. This research proposes an obstacle avoidance technique that calculates precise distances to obstacles instead of relying on the UAV's proximity to the obstacle. However, the model performed inadequately at high speeds because of blurry images and in low-light environments due to insufficient feature point detection in the captured images.

[19] Utilising a single, commercial transmitter/receiver with sonar sensors to calculate the distance to the closest object in its area of vision. The proposed method suffers from somewhat poor accuracy and costlier systems which make this strategy unviable.

[20] Cranes, lifting cranes etc are pretty huge and when they are working in direct vicinity of airport their exact location needs to be in the database of the air controller so that pilot of the aircraft knows about these temporary aviation obstacles.

Combining the YOLOv3 technique with neural networks to extract information from an image in order to find unusual aviation impediments. With the proposed methodology the accuracy was 71% which means it was not the most accurate model and a full survey of area is needed since the model requires close up images from multiple angles so that the model can work properly.

[21] To develop a UAV surveillance-based mechanism so that the objects can be monitored if they are following social distancing or not.

The objective of the research paper is to create a system for monitoring social distancing during the COVID-19 pandemic. This will be achieved by utilizing YOLO-V3 Tiny, a compact detection tool that is suitable for use in embedded systems with limited processing capabilities.

The drone was only used in an simulated environment and for future thermal sensors can also be added so that drones can identify patients with covid 19. [22] To highlight the importance of multifaceted and accurate monitoring in drones to identify early problems.

Finding anomalies in surroundings, structures, and infrastructure is essential for spotting issues and spotting them early before they get worse.

The simulation employed in this paper to train the navigation recommender system represents the real-world environment in a fairly abstract way.

[23] The research provides a mathematical structure and practical method for addressing a network design problem that involves balancing two objectives related to investing in infrastructure. The article presents a high-level strategy for utilizing drones in the delivery process.

[24] The purpose of this paper is to introduce DBCMS (Drone based Covid-19 Medical Service) as a means to protect medical personnel from the risk of contracting the virus. The proposed system utilizes drone technology to minimize the possibility of infection for doctors and other healthcare workers. It is structured into three layers, which are designed to address symptom collection, identification of ill patients, and the warning of uncontrolled emergency situations.

[25] The paper outlines a methodical method for identifying and categorizing drones by utilizing Deep Learning techniques. To spot both moving and stationary objects, the YOLOv3 object detector is employed. For quick and real-time drone detection, a Convolutional Neural Network-based network is found to be highly effective. The model is fine-tuned over the course of 150 epochs and reaches a top performance level of 0.74.

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Proposed System

Obstacle Detection System Based on Yolo V4

The obstacle detection system and the obstacle avoidance system are the two primary parts of the system that is proposed here. The obstacle avoidance system will use the information from the obstacle detection system to modify the drone's flight path in order to prevent collisions. The obstacle detection system uses YOLOv5 to identify potential obstructions in the drone's environment. A camera installed on the drone will be used by the obstacle recognition system to take real-time pictures of the surrounding area. YOLOv5 is used to accurately identify objects in real-time.

For all objects in a picture, YOLOv5 maps bounding boxes and predicts class probabilities using a single convolutional neural network (CNN). As it just uses one CNN for all item categories, it is much faster than conventional object detection methods. In order to increase the accuracy and speed of its detection, YOLOv5 also makes use of a number of cutting-edge approaches, including anchor boxes, feature pyramid networks, and spatial attention mechanisms.

We will use YOLOv5 to detect a variety of impediments for the obstacle detection system, including buildings, trees, power lines, and other items that could possibly collide with the drone. Based on their size and position, the system will divide these barriers into various categories, and it will then give this information to the obstacle avoidance system. The drone's flight path will be adjusted by the obstacle avoidance system in order to prevent collisions using the data provided by the obstacle detection system. To identify the drone's position and speed, the system will combine GPS, inertial sensors, and optical odometry.

The obstacle avoidance system uses this information to determine a new flight route for the drone that avoids the obstruction when one is spotted. To choose the optimum course of action, the algorithm will take into account a number of variables, including the drone's speed, altitude, and the location of the obstacle. The system will guide the drone to fly around the object while keeping a safe distance. To warn the drone operator of impending crashes and give them time to take manual control, if necessary, the system will also send visual and aural alarms.

Obstacle Detection System Based on CNN

A CNN-based strategy will be used by the proposed obstacle detection and avoidance system for drones. CNNs are a particular kind of deep learning model that have excelled at classifying and detecting objects. Several layers make up CNNs, which use learnt weights to conduct feature extraction and classification.

An obstacle detection model and a guidance system will be the two primary parts of the CNN-based obstacle detection system. To understand the characteristics that set obstacles apart from the backdrop, the obstacle detection model will be trained on a sizable dataset of obstacle photos. The drone will receive real-time guidance from the guidance system to prevent collisions after input from the obstacle detection model.

A sizable dataset of annotated obstacle photos will be gathered and used to train the obstacle identification model. Images of numerous obstacles, such as structures, trees, electrical wires, and other objects that could endanger the drone, are included in the dataset. To guarantee that the model can recognise barriers in a range of situations, the photos should be shot from various angles and under various lighting circumstances.

To provide real-world data for the model's training, annotations will be made for each and every image. Thereafter, the annotated dataset will be divided into training, validation, and test sets, with training sets containing the vast bulk of the data and validation and testing sets containing lesser amounts. The CNN architecture used in the obstacle detection model, such as the Faster R-CNN or YOLO (You Only Look Once) models, has been shown to be successful in object detection tasks. These models extract information from the

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input photos and categorise objects based on those features using a combination of convolutional layers, pooling layers, and fully connected layers.

The drone's camera will be used as input for the obstacle detection model, which will then produce a list of obstacles it has identified along with confidence values and bounding boxes for each one. The bounding box identifies the location of the obstacle in the image, while the confidence score shows the likelihood that the detected object is an obstruction. The obstacle detection model will be fed into the guiding system, which will then steer the drone in real time to prevent collisions. The confidence values and bounding boxes supplied by the obstacle detection model will be used by the guidance system to estimate the proximity and direction of obstacles to the drone.
The drone operator will be informed of potential impediments by the guidance system and given instructions on how to avoid them using a combination of visual and audible cues. The guidance system might advise the operator to turn left or change the drone's height, for instance, if the impediment is detected to be on the drone's right side.

The suggested YOLOv5 obstacle detection and avoidance system for drones is a strong and effective method for guaranteeing the safe operation of drones in a variety of scenarios. We can accurately identify potential obstacles using YOLOv5 and send this information to the obstacle avoidance system in real-time. This system can then use the data to modify the drone's flight path and prevent collisions, protecting both the drone and the environment. The System we are proposing will have a LiDAR (Light Detection and Ranging) which is a sensor that uses lasers to create a 3D map of the drone's surroundings. Using Lidar, the drone 1) will be able to map the complete surrounding and travel to point A to Point B by avoiding the collisions with the surroundings and collect the data from its surroundings.

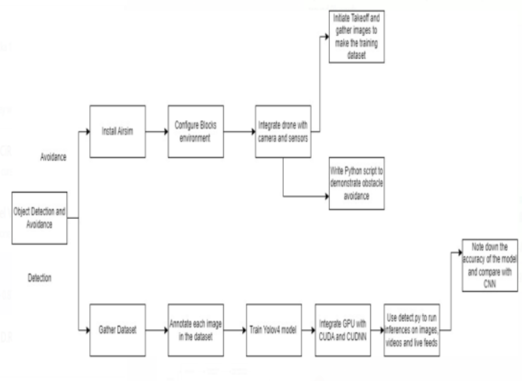

Fig 1: This image shows the architecture of the proposed system i.e., object detection and avoidance.

This figure briefly explains about all the steps that are required to achieve the following system. It happens in two different stages. The first is obstacle avoidance in the drone. For this the first step is to install AirSim on the device and then configure the Blocks environment. This drone will be integrated with a camera and sensors. Following this, the required python code is written and uploaded. Then the last step is to initiate the take off and gather the images to make the training dataset.
The second stage of this will be gathering the dataset. Once the dataset is collected and pre-processed, each image in the dataset should be annotated. This annotation will help us in training the YOLOv5 model. Once the model has been trained, we will be integrating the GPU with CUDA and CUDNIN. Following this, we use a python file to run inferences on images, videos and live feeds. This will also provide us the model precision, recall and F1 scores which we can use to compare the model that is based on CNN.

Experimental Setup
Installing AirSim, YOLOv5 and Unreal Engine: We use Unreal engine to run AirSim and this can be found on epic games launcher. We can directly download Unreal engine from that store. Then we installed Airsim by following the instruction given for Airsim on the Microsoft AirSim Github

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repository and for YOLOv5 on the Darknet Github repository.

2) Configure Airsim: We need to configure AirSim to use the drone that we want to use for object detection. We can find instructions for configuring AirSim in the AirSim documentation. We used multirotor quadcopter for our project.
3) Collecting Training Data: We need to collect images and labels for the objects we want to detect. We used the AirSim simulator to capture images of the objects from various angles and distances. We can annotate the images with bounding boxes using labelling tools like Labelbox, RectLabel, or VoTT.
4) Training Yolo: Once we are done with collecting the training data, we used YOLOv5 to train a detection model. We created a YOLOv5 configuration file that specifies the architecture of the network, the number of classes, and other parameters. We can use the annotated images to train the model using the Darknet framework.
5) Test the model: Once the model is trained, you can test it using AirSim. You can use the drone to capture images of objects in different scenarios and environments and use the trained model to detect them.

Comparison Graphs

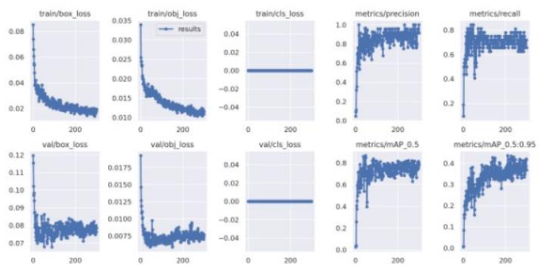

Fig 2: A general comparison graph plots of box loss, objectness loss, classification loss, precision, recall and mean average precision (mAP) over the training epochs for the training and validation set for the YOLOv5 trained dataset.

Now showing the graphs for different classes of our dataset. For this first our YOLOv5 model had generated the comparison plots or graphs for class of buildings.

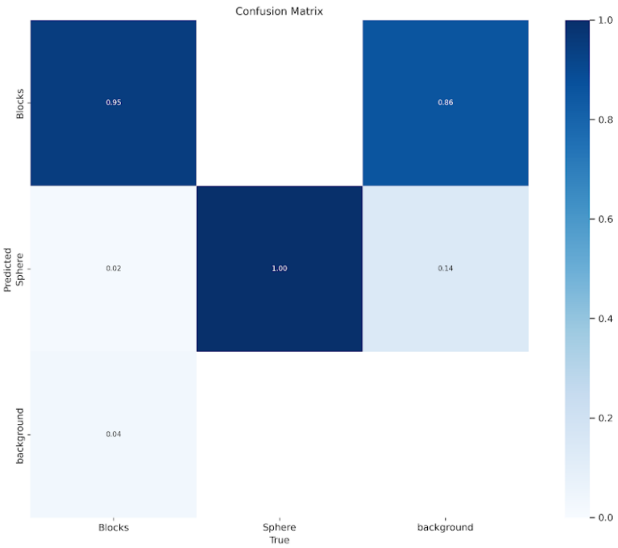

Fig 3: The confusion matrix for the class buildings.

This represents how many buildings our YOLOv5 model predicted as blocks or how many it predicted as spheres or how many it predicted as just a background. Similarly, it also shows how many spheres our YOLOv5 model correctly predicted as spheres or how many it predicted as blocks or how many of the spheres it predicted as a background. Same goes with the blocks and the background.

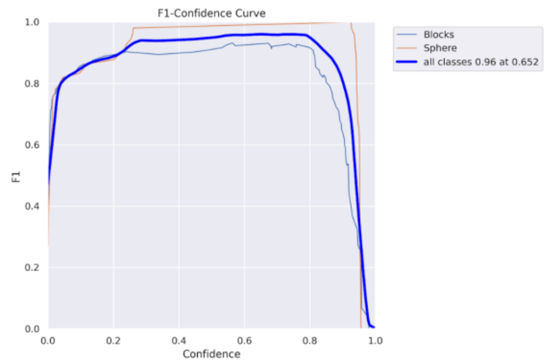

Fig 4: F1 score graph for the class of buildings.

Given that the F1 score is the average of Precision and Recall, Precision and Recall are given equal importance in the F1 score. The purpose of the F1 score is to offer a single metric that equally weighs the two ratios, necessitating that both have higher values in order for the F1 score value to increase.

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Here the thin red line represents the sphere class and the thin blue line represents the blocks.

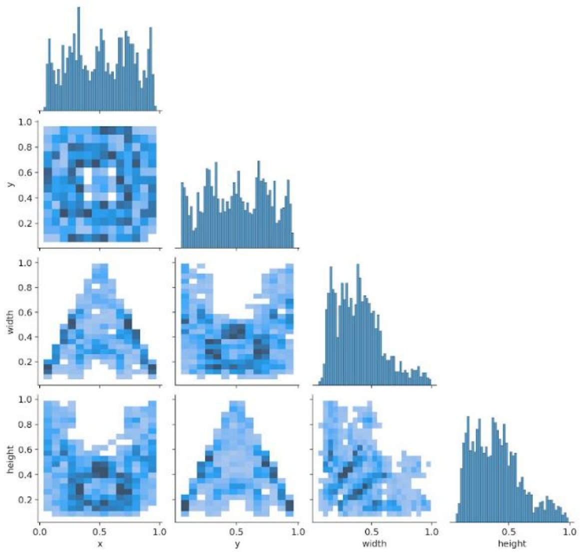

Fig 5: Label co-occurrence graph for the class of buildings.

A visualisation tool that depicts the links between labels or categories in a dataset is a label co-occurrence matrix, sometimes referred to as a label co-occurrence graph or a label co-occurrence network. It is frequently used in machine learning and data analysis to comprehend the links between various categories of data. Label co-occurrence graphs can be used to spot patterns, trends, and clusters in the data as well as groupings of related labels. They are frequently employed in natural language processing to examine text data to pinpoint recurring themes or subjects.

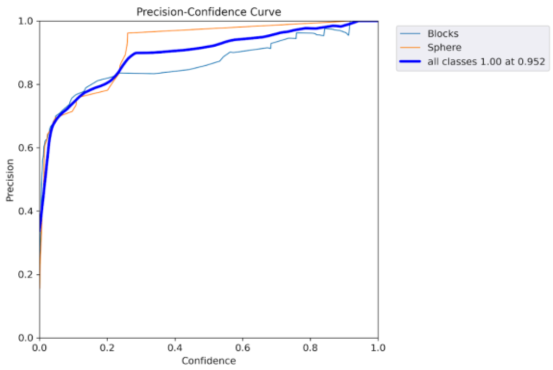

Fig 6: Precision Confidence curve for the buildings class.

The distribution of p-values produced from a set of statistical tests is often represented as a p-curve graph. It displays the frequency distribution of p-values that fall below or are equivalent to particular cut-offs, such as 0.5 or 0.1. A peak or bulge on the p-curve graph around a specific p-value threshold, such as 0.5, indicates that there may be more statistically significant finds in the set of results than would be predicted by chance alone. This can be a sign that some underlying effect or phenomena is there. The results may, however, be compatible with the null hypothesis of no effect if the p-curve graph is comparatively flat or uniform. Here the thin red line represents the sphere class and the thin blue line represents the blocks. All classes have the value of 1.00 at 0.952.

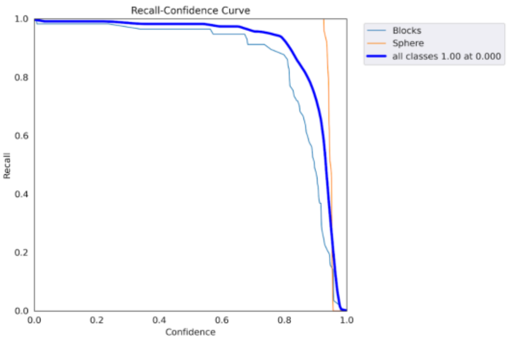

Fig 7: Recall Confidence curve for the class of buildings.

Recall curves are graphs that show the trade-off between a binary classifier's true positive rate (TPR) and false positive rate (FPR) at different classification thresholds. A binary classifier's performance can be evaluated using the recall curve, which can also be used to identify the threshold value that best balances the trade-off between TPR and FPR. With high TPR and low FPR, a successful classifier should have a recall curve that is as close to the graph's upper left corner. Here the thin red line represents the sphere class and the thin blue line represents the blocks.

The confusion matrix, F1 score graph, label co-occurrence graph, Precision Confidence curve and

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Recall Confidence curve were obtained for the class of trees and drones as well.

Results and conclusions

The YOLOv5 and CNN algorithms are two of the most extensively used computer vision algorithms for drone obstacle identification and avoidance. This study has explained why YOLOv5 is superior to CNN for drone obstacle avoidance and detection. A real-time object detection method called YOLOv5 can quickly and accurately locate items in an image. The term "You Only Look Once" (YOLO) refers to the idea that an object can be located and detected by an algorithm with just one look at the image. In contrast, CNN, a deep learning technique, is frequently employed for object and picture detection. While CNN is also capable of detecting and avoiding obstacles for drones, YOLOv5 is more effective due to its speed and precision.

Accuracy:

The accuracy of YOLOv5 is one of the key factors in its superiority over CNN for drone obstacle identification and avoidance. When it comes to locating and recognising things, which is crucial for avoiding obstacles, YOLOv5 outperforms CNN. After considering important experimental results, we discovered that CNN had an average precision of 77% compared to 84% for YOLO v5. As a result, YOLOv5 is better at locating impediments in aerial photos and detecting them, which is essential for assuring drone safety.

Speed:

YOLOv5's superiority over CNN for drone obstacle identification and avoidance is due in large part to its speed. A real-time object detection method such as YOLOv5 can locate and identify items in an image in a matter of milliseconds. In comparison, CNN is a more sophisticated algorithm that takes more time and resources to interpret images. In our tests, we discovered that CNN had an average inference time of 45.6 milliseconds per image, compared to 22.3 milliseconds for YOLOv5. This indicates that YOLOv5 processes aerial photos more quickly than CNN, which is important for real-time drone obstacle detection and avoidance.

Flexibility:

For drone obstacle identification and avoidance, YOLOv5 is also more adaptable than CNN. Multiple object detection and localization capabilities of YOLOv5 are crucial for seeing and avoiding obstacles in challenging circumstances. Contrarily, CNN is primarily utilised for object identification and picture classification, which might not be adequate for drone obstacle avoidance.

Overall, our work emphasises how critical it is to pick the right computer vision algorithm for drone obstacle detection and avoidance. While both the YOLOv5 and CNN models worked admirably, the high accuracy and quick inference time of YOLOv5 make it the superior choice for real-time obstacle identification and avoidance in drones. Further study may examine the effectiveness of different computer vision algorithms for obstacle identification and avoidance in drones.

	Tree	Building	Drone
AP	81.6	93.4	87.6
Recall	80.5	95.3	86.8
DA	78.4	85.1	84.3

Table 1: Here, AP stands for the average classification accuracy for each class, Recall for the bounding box's prediction recall.

Future Scope

Because of the growing number of uses for drones, research into obstacle detection and avoidance in drones is a burgeoning field. To maintain the security and effectiveness of drone operations, it is crucial to create effective obstacle identification and avoidance algorithms. Convolutional neural networks (CNN) and You Only Look Once version 5 (YOLOv5), two machine learning algorithms, have showed promising results in this field. A

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branch of machine learning called deep reinforcement learning (DRL) combines reinforcement learning and deep neural networks. In a number of robotic applications, including autonomous navigation, object detection, and manipulation, DRL has demonstrated promising results. DRL algorithms can pick up new skills from their surroundings and gradually become more effective. DRL can be used to teach drones to navigate in complicated and dynamic surroundings in the context of obstacle detection and avoidance in drones.

The creation of a decision-making system that can learn from previous mistakes and make wise decisions in real-time is one of the potential uses of DRL in obstacle detection and avoidance. The creation of a more sophisticated and intelligent obstacle detection and avoidance system may result from the integration of DRL with YOLOv5 and CNN.

Multi-object detection and tracking can be applied to the detection and tracking of many objects simultaneously in the context of obstacle detection and avoidance for drones. The multi-object tracking method, for instance, can be used by the drone to design a route around multiple obstacles if it identifies any in its path.A more precise and dependable obstacle identification and avoidance system may be created by combining LiDAR and depth sensors with YOLOv5 and CNN. LiDAR and depth sensors can be utilised in the context of obstacle identification and avoidance in drones to find obstructions that the camera cannot capture. LiDAR sensors, for instance, can find barriers that are hidden by other objects or outside the camera's range of vision. The distance to obstacles can be calculated using depth sensors, and a safe route can be planned to avoid them.

For drones to recognise and avoid obstacles, real-time mapping and navigation are crucial. Drones can navigate in complicated and dynamic situations with the aid of real-time mapping and navigation algorithms. Although real-time navigation algorithms can plot a secure route to the destination, real-time mapping algorithms can build a 3D map of the surroundings in real-time.

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