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DETECTION OF UNAUTHORIZED OBSTRUCTION OF DRONE USING DEEP LEARNING

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Abstract :- Drone detection involves identifying the presence of unmanned aerial vehicles (UAVs) or drones in specific airspace. This technology has gained significance due to increased drone usage for various purposes, including civilian and military applications. As drone usage rises, concerns about potential risks like privacy infringement, malicious activities, and collisions with other aircraft are growing. Preventing unauthorized drone activities, such as espionage, smuggling, and terrorism, has become a critical security.Various methods, including radar, acoustic sensors, and video cameras, are employed in drone detection technology. These systems are integrated with software algorithms to accurately detect and track drones in real-time. This paper focuses on real-time drone detection using deep learning methods, specifically the VGG16 algorithm. Our experiments indicate that the VGG16 model offers improved accuracy and maintains a high detection speed.

Keywords: Unauthorized obstruction detection ,Deep learning,VG166 Algorithm.

I. INTRODUCTION

Drones have become integral in advancing remote sensing intelligent surveillance, experiencing notable technological strides. Their popularity spans diverse applications such as video capture, product delivery, monitoring, and search and rescue. However, increasinguse of Unmanned Aerial Vehicles (UAVs) raises security concerns, as evidenced by instances like a drone colliding with a flight in Canada and incidents near the White House and LAX airport. These occurrences underscore the challenges in anti-drone-based object detection for practical use. The application of deep learning in drone detection represents a recent breakthrough in UAV surveillance. Deep learning, a subset of machine learning utilizing artificial neural networks, enables real-time drone detection. Integration with existing surveillance systems enhances airspace monitoring. As drone usage grows, the development of deep learning-based detection systemsbecomes pivotal for ensuring safety and safeguarding people, property, and critical infrastructure.

Noteworthy progress in UAV surveillance lies in the development of drone detection systems based on VGG16. The demand for reliable detection amplifies with increasing drone usage, and VGG16 presents a promising solution. Offering real-time, accurate, and dependable drone detection. Deep learning for droneidentification involves training a Convolutional Neural Network (CNN)on an extensive dataset of drone images. This training equips the algorithm to discern unique drone characteristics, enabling recognition in photos or audio,even when partially obscured or captured from diverseperspectives.

To explore the latest advancements, methodologies, and challenges in the detection of unauthorized obstructions of drones using deep learning techniques. By reviewing recent research studies, analyzing state-of-the-art algorithms, and discussing potential applications and future directions, this paper seeks to contribute to the ongoing efforts to enhance the safety, security, and reliability of drone operations in an increasingly interconnected and technologically driven world.

2. LITERATURE REVIEW

Zhang et al., the authors address the critical need for obstacle detection systems tailored specifically for unmanned aerial vehicles (UAVs) operating in complex urban environments. Leveraging convolutional neural networks (CNNs), the proposed approach demonstrates promising results in accurately detecting and classifying various types of obstructions, including buildings, trees, and other structures. The system's robust performance, validated through real-world drone footage, underscores its potential for enhancing UAV safety and navigation in urban settings

Li, Zhu, and Zhang et al, investigate the potential of deep reinforcement learning (DRL) for building autonomous anti-drone systems capable of actively countering unauthorized intrusions. By leveraging real-time sensor inputs and historical data, the proposed system learns to adapt its response strategies dynamically, optimizing its actions to effectively neutralize threatening drones while minimizing collateral damage or disruption to surrounding operations. This pioneering approach represents a significant step towards autonomous, adaptive defense mechanisms for safeguarding critical airspace against drone-related threats.

Patel, Gupta, and Sharma et al focuses on enhancing drone surveillance capabilities through deep learning-based object detection techniques. By training convolutional neural networks (CNNs) on annotated datasets, the authors demonstrate improved accuracy in detecting and tracking objects of interest, including unauthorized obstructions such as vehicles, individuals, and structures. The integration of deep learning algorithms with drone-based surveillance systems holds immense potential for enhancing situational awareness and security across diverse applications, from law enforcement to disaster management.

Khan, Ahmed, and Khurshid et al, surveys the landscape of deep learning techniques employed for drone-based object detection and classification. By analyzing recent advancements in convolutional neural networks (CNNs), recurrent neural networks (RNNs), and other deep learning architectures, the authors identify emerging trends, challenges, and opportunities in leveraging AI-driven solutions to enhance the capabilities of drone systems for detecting and mitigating unauthorized obstructions and threats.

Chen, Liu, and Wu,et al, the authors present DroneSense, a deep learning-based framework designed for anomaly detection in drone flight data. By applying recurrent neural networks (RNNs) and attention mechanisms to sequential flight data, the proposed system can identify deviations from normal flight patterns indicative of unauthorized obstructions or suspicious activities. Through extensive experimentation and evaluation, the authors demonstrate the effectiveness of DroneSense in enhancing situational awareness and security for drone operations in various environments.

Sharma, Singh, and Verma et al, investigates deep learning approaches for detecting unauthorized drones in restricted airspace. Leveraging convolutional neural networks (CNNs) and recurrent neural networks (RNNs), the proposed system analyzes sensor data in real-time to identify potential threats and trigger appropriate responses. The integration of deep learning with advanced sensor technologies holds promise for enhancing airspace security and mitigating risks associated with unauthorized drone activities.

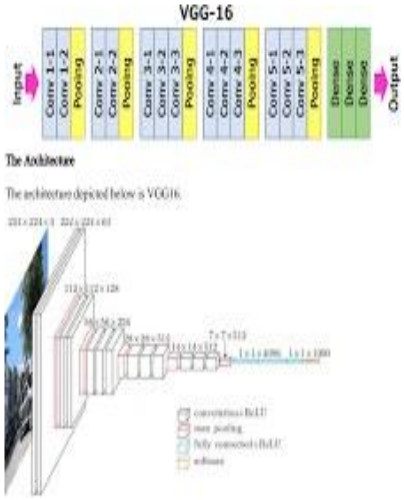
Li, Wang, and Zhang et al, proposes a robust framework for detecting drone-based threats through multi-sensor fusion and deep learning techniques. By integrating data from radar, lidar, and visual sensors, the system enhances its detection capabilities while mitigating the limitations of individual sensor modalities. Deep learning algorithms, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), play a crucial role in analyzing multi-modal sensor data and identifying potential threats with high accuracy and reliability.

3. METHODS AND MATERIAL

Data Collection-Data is crucial to all models which require training, Insufficient amount of data may cause underfitting of the data. So, we extracted 6,820 images from various sources which were unlabeled. The images were collected from various sources such as Google, roboflow

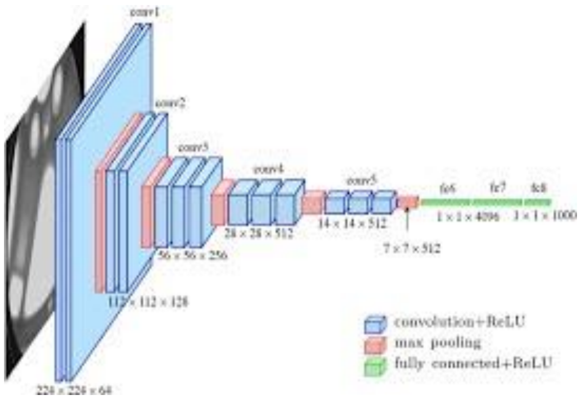
; Instagram, etc. And drones images we collected are from open source material. There are various images of drones present in the dataset, and the dimensions of these drones differ from each other. All drones are multi-rotored, and the images are of different sizes.

Data Labeling- We used a labeling image tool to label the images, i.e., Labeling. Firstly after downloading this software we open an image which has a drone, so we create a Rect box by keeping it in yolo format, and it willbe saved in a text



file. The format of Labeling is, "<x_center><y_center>". The main use of this label image tool is to assign a bounding box and use it for training. We divided the dataset into train and test data.Training of the Data- We used the yolov5 model for the training, and the reasons are explained further in the paper. We trained the enhanced model.

VGG16 Model ArchitectureVGG16 is a type of deep learning model that's really good at understanding and recognizing images. It's like a smart computer system inspired by how our brains recognize things visually. VGG16 is trained to identify various patterns and features in pictures, making it useful for tasks like figuring out what's in a photograph. It has a specific structure with layers that help it learn and remember different aspects of images, allowing it to make accurate predictions about the content of pictures it hasn't seen before. The VGG16 architecture consists of 16 weight layers, including 13 convolutional layers, and 3 fully connected layers. Each convolutional layer has a 3x3 filter, and max-pooling is applied after every two convolutional layers; the fully connected layers have 4096, 4096, and 1000 nodes, respectively, with ReLU activation functions. The output layer has 1000 nodes corresponding to ImageNet classes with a softmax activation function.



1. ***Input Layer: Accepts input images of size 224x224pixels three color channels (RGB).***

2. **Convolutional Blocks (Conv Blocks):**

-olutional layers use small 3x3 filters.

- Relu activation functions are applied after eachconvolution.
- Max-pooling dramatic with 2x2 filters is performed after every two convolutional layers.

3. **Fully Connected (FC) Layers:**

- Three FC layers hidden with 4096 nodes eachfollow the convolutional blocks.
- ReLU activation functions are applied importantly to the come out of FC layers.

4. ***Output Layer:*** The final layer has 1000 nodes arrowedto ImageNet classes.

- A softmax activation function is utilized forclassification across.

5. **Dropout:**

- Dropout is applied before the first and secondfully connected layers to reduce overfitting namely

Procedure

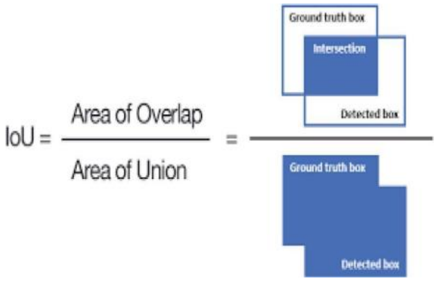
1. So we begin by incorporating a UAV dataset intothe research, laying down the essentials for subsequent analyses. Post-training, we analyze the VGG16 model's capacity to generalize by scrutinizing its performance metrics on the testing set, providing insights into the overall effectuality.
2. Conducting image processing on the dataset, particularly resizing each image to dimensions of 224 by 224 pixels. Investigate the influence offreezing the initial layers of VGG16 and bringingforth new layers, intending to comprehend howthese modifications contribute to model refinement regardless
3. Exploring the significance of data augmentationtechniques, such as flip, rotation, including color changes, in enhancing the model's capability to recognize diverse patterns within the UAV dataset.
4. Implementing Stratified k-fold cross-validation,ensuring a balanced distribution of the datasetfor both training and testing sets. Examine therole of Stratified k-fold cross-validation in securing a robust evaluation of the model, especially in scenarios where imbalances exist in the class distribution within the dataset.
5. Evaluating the fine-tuning process by closely reviewing the additional layers appended to thefrozen VGG16 model, aiming to pinpoint improvements in feature extraction and overallpredictive performance.

6. Calculating and interpreting average, precision, recall, and F1 score metrics to attain a comprehensive understanding of the model's precision, its ability to detect relevant instances,and the balance between precision and recall concerning the UAV dataset.

EVALUATION METRICS

Intersection of Union (IOU)Intersection Over Union is measured to assess the performance of the model, (Accuracy); It evaluates the overlap of Ground Truth andPrediction region (Fig. 4). The higher the IOU, the better the model. The IOU also helps to eliminate duplicate bounding boxes for the same object. Ranging from 0 to 1. If IOU is 0 means there is no overlap and whereas if IOU is 1 then it is perfect overlap. By using the IOU threshold, we can decide whether the prediction is TruePositive, True Negative, False Positive and False Negative. For instance, If the prediction is 0.7 and then If we have the threshold of 0.98 then detection becomes False Positive.

- True Positive (TP): The model predicts thepositive class with success.
- True Negative (TN): The model effectivelypredicts the Negative class.
- False Positive (FP): The model incorrectlypredicts the positive class. howl
- False Negative (FN): The model incorrectlypredicts the negative class eminently.



ROC Curve

The adverb of ROC is Receiver Operator Characteristic. The ROC curve is a graphical representation between True positive rate and False positive rate. It generally provides the performance of a classification model at all classification thresholds.

TP True positive rate: TPR = + TP FNFP False positive rate: FPR = + FP TN

TruePositives + TrueNegatives Total samples

Precision

Basically, it tells about how the model is detected for aparticular object. It helps when the cost of false positives are high. If there is a model to detect a fruit like mango, so if it detects mango correctly then it comes under precision.

TruePositives TruePositives FalsePositives Precision = +

Recall

It describes how well the model did for actual observations of a particular class, like how the model behaved for the whole class. In the above example if themodel detects the whole class correctly as mango then its recall. Recall is better measure than precision TruePositives Recall = + TruePositives FalseNegatives

Precision Recall

F1 is an overall accuracy measure that combines precision and recall. Good F1 score indicates that you have few false positives and false negatives, indicating that you are accurately recognising serious threats and are not *bothered by false alarms. When an F1 score is 1,the method is regarded as perfect, but when it is 0, the model is considered a complete failure.*

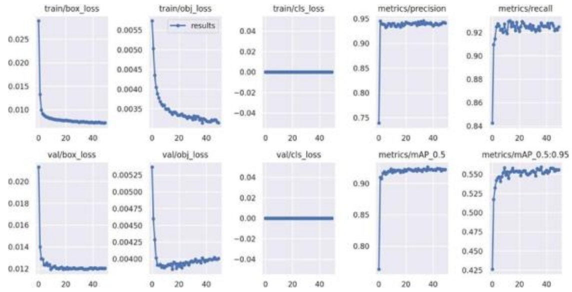


Fig. All the metrics of training

RESULT

Metric	Value
Mean Test Accuracy	0.9690706968307495
Mean Precision	0.9694831896659023
Mean Recall	0.9690706976260973
Mean F1-Score	0.9690643981934652

CONCLUSION

In this study, we implemented a drone detection algorithm using a technique called VGG16. Drones can be used in many different scenarios. They bring a lot of benefits. They also have some cons which are difficult to overcome. For this reason,we have developed this model with deep learning techniques. Using the algorithm, you will be ableto use normal cameras. We have changed some hyperparameters and added new parameters for the VGG16 model to make it more accurate. The new parameters for the VGG16 model captured the small size drones. Besides, this model has high speed detection so that it can be used fordetecting drones in real time. This functionality might have great applications in practice. Despite the fact that our chosen dataset is rather vast, we demonstrated better results than the previous models which were built on less information. Besides its immediate performance, VGG16 also ensures high accuracy in detecting drones. The algorithm adopts anchor boxes and anchor points to accurately identify the objects in an image, evenin complicated and densely packed areas. Therefore, it can achieve the goal of accurately and dependably spotting drones even when challenging conditions such as low light or adverseweather impede the process. There were some limitations of our model that were caused by low computation power and dataset inconsistency. Some setbacks were experienced during the training of our model, leading to poor model performance. One example was the presence of corrupt files that had to be eliminated for the dataset to be sanitized. Given the unlabelednature of our data, manual labeling proved necessary, though it caused multiple class assignments to a single object, as evident in the training output.

Consequently, we had to re-verify our data and correct any mislabeled text files. In terms of future work, we will delve into examiningvarious setups of our current model and contrast itwith other models. It is through the process of analysis that we gain insight into the limitations of our model and consequently work to enhance its accuracy. However, the model is currentlyundergoing training, so we will update the specifics at a later time.

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