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Research Paper

Drone Detection and Tracking System

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Abstract:-
Drones to play an important role in the smart cities in the future. They will deliver goods and goods, act as mobile hotspots for broadband wireless access, and manage surveillance and security in smart cities. While drones can be used for human development, they can also be used by malicious organizations to carry out physical and cyber-attacks and harm society. The growing popularity and use of unmanned aerial vehicles (UAVs) or drones has raised concerns about the potential security threats they pose. Overall, this article aims to provide a method that can solve the problem of drone detection. To maintain the security and safety of the general population, it is crucial to develop an effective and trustworthy drone detecting system.

Keywords:-
- *Yolov4*
- *Python*
- *Deep-Net*
- *Darknet*
- *CNN*
- *Drones/UAVs*
- *OPEN CV*

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I. Introduction:-

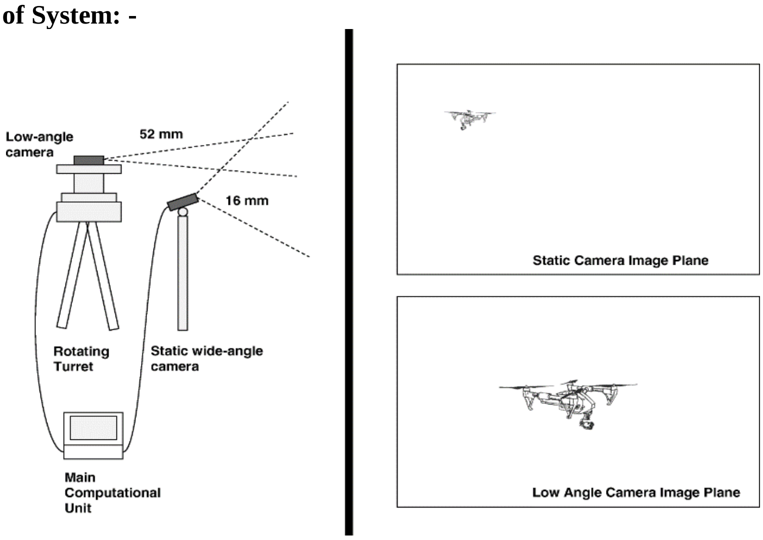
In recent years, unmanned aerial vehicles (UAVs) or drones have gained popularity due to their versatility and ease of use. However, their increased use has raised concerns about their abuse, especially in restricted weather conditions. To solve this problem, a drone detection system has been developed to detect and track illegal unmanned aerial vehicles. Traditional detection methods such as radar, acoustic sensors and cameras have proven to be effective to some extent, but their accuracy and reliability can be further improved using machine learning (ML) ideas. In this research paper, we propose a new drone detection system that uses the latest machine learning techniques such as YOLOv4, Deep Net, Darknet, Robo flow and Python. The proposed system uses a combination of object detection and tracking algorithms to identify and track UAVs in real time. YOLOv4 is used for object and local search, while Deep Net and Darknet are used for extraction a nd classification. Robo Flow was used to preprocess and insert training data, while Python was used to create th

e system's user interface and real-time animation.
We evaluate the performance of the proposed method on a large dataset of drone footageand video. The results show that the proposed method achieves high detection and tracking accuracy while maintaining low cost. Additionally, we demonstrate the superiorityof our method by comparing the performance of our system with c urrent drone detection.
Overall, this research paper presents an effective method for drone detection using machine learning algorithm s. The proposed systemcan be used for a variety of applications, including the protection of critical infrastructur eborder security and public security to ensurethe safety of drones. The rapid growth in thesize of the drone indu stry has made these devices affordable and accessible to the general public.The drone can be turned into a deadl y weapon by being loaded with explosive
Detector performance degrades due to lighting, changes in vision, and the angle of the object in the camera. Mo st objects cannot be captured when the object is deformed or the object's scale change.

Previous Models & existing models.
The systems and training materials proposed on the market can be grouped according to their equipment: radar, lidar, acoustic, radio frequency signal and optics.
radar technology has been used to detect aircraft for decades; However, conventional drones cannot catch small business drones. Additionally, they fly at low altitude, which distorts the Doppler signal. When samples do occu r, they often fail to follow other aircraft objects such as birds and background clutter, especially in the K, S, X b ands, and when using the Doppler effect because they are sensitive to this feature [16]. Therefore, radar technol ogy was not considered a good solution-drone, especially for autonomous installations.
Lidar is a new technology for dronesurveillance missions, so only some of these recommendations are available in the literature. Its efficiency and cost-
effectiveness are still questionable for reasons such as big data throughput and sensitivity to the cloud. Perhaps t he most popular method in the drone detection industry is radio frequency signal targeting, designed to ca pture communication between the drone and the operator on the ground. However, the main problem of this met hod is that the drone can operate uncontrolled from the ground with the flight path ahead. The Acoustics also captures drones using a microphone array.

That's why we look at a model for commercial cameras as the only or at least one sensor of the concept system. In addition to the advantages mentioned above, the use of optics has similarities with recent developments in de ep learning computer vision algorithms. Finally, with open data (e.g. images, videos), advanced algorithms and inexpensive GPU programs, deep learning for computer vision using convolutional neural networks (CNN) has become a real approach to research and knowledge studies.

Main Architecture of System: -



As shown in Figure 1, our hull consists of a static wide angle camera (adjust the angle and position as needed), a rotating turret mounted with a narrow angle zoom RGB camera, and a mainframe mounted on a fixed platform. Based on the modified lightweightYOLOv4 architecture, we capture the smallest users. In the first stage, a negative measure can be considered if they are tracked and analyzed by rotating the turret based on their strength and visual signature and observed with a narrow camera. Due to Python's versatility and performance, Our system uses python as the main language.

The deep learning system for detection and classification is based on the Darknet YOLO architecture, which is written in C but can be wrapped in python.

At first, the system tries to detect small drones, viewing the horizon using a wide angle camera. In accordance with the square input image of the YOLO architecture, we first reshape the raw image from the wide angle camera to 1600 × 1600 pixels.

We chose to use YOLO, which is the first choice of many researchers for search and classification due to its hig h performance and speed [26]. Unlike other image search methods of neural networks, YOLO uses the method t o recover local objects of the image which makes the process faster. In the latest version of YOLO (YOL Ov3), a new conceptcalled upsampling was introduced that greatly improves the detection of small obj ects. In this release, the oversampling layer is included in the layers of the architectur-
e with image plane size reduction.
The feature matrix is up-sampled by ×2 and
connected to the previous layer (which has the same feature size asthe new upsampling layer) via a routing lay er. To be clear, this is an attempt to control the small sample size by rescaling the eigenvectors of the position a xis. The default version of
YOLOv3 has a total of 102 layers, including3 detection layers each corresponding to the directory. That is, after the first detection
layer, the characteristic matrix is doubled.
The default version has two different input size options, 418 × 418 and 627 × 627. The YOLO detection operati on can be viewed asa regression function that localizes objects in probabilistic manner.
To achieve high AP and FPS, **YOLOV4** integrates new features (including WRD, CmBN, CSP, SAT, mosaic data augmentation, Mish activation ,Drop Block normalization and loss of CloU).

Yolov4 conducts its search in four stages: the introduction, the back, the neck, and the bold guess or head. The dataset we wish to record is input. The backbone is in charge of extracting information from image collections and using them to create quantifiable and potent objects. It is split into three parts: CSP-Darknet53, special bags, and gift bags. Similar to YOLOv3, the head of Yolov4 employs the same idea.

The end effect is an increase in contrast so that the capture model is not hindered by the uncertain location. To correct the photometric distortion, the image's contrast, brightness noise, and saturation are then adjusted.

1.) Bag of freebies:-

BOF is a plan for offline training of seized items without growing up the imagination. There are many ways available in computer vision by which we can achieve the BoF target, but YOLOv4 uses specialized techniques, including bones and detectors.

Key technologies of BoF used in YOLOV4 are tag smoothing, Cut Mix mosaic data augmentation, regular Drop Block and IoU loss. Object detection models' capability is increased by using data augmentation. The end result leads to the increase of the image contrast,so that the unknown location is not a problem for the capture model. This is followed by adjust the brightness, contrast saturation and noise of the image to overcome the problem of photometric distortion.

BoF uses loss of focus (FL) to solve the problem of inconsistent data. In classification problems, the use of cross-entropy (CE) properties loses its effectiveness; however, it does not handle the wrong things well. Thus, FL was introduced, which replaced CE. An additional coefficient (1-pt)t is used in FL.

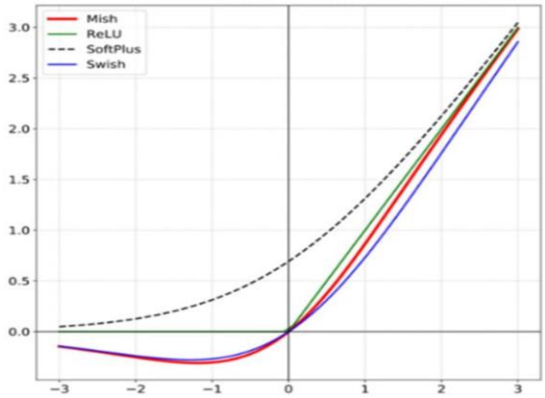
2.) Bag of Strategies:-

By introducing a thin layer of inference cost known as BoS, YOLOv4 increases the accuracy of object detection. Many things are combined to achieve BoS, but the most notable improvements include enabling Mish, CSP connectivity, SPP block and PAN integration method. To make Mish account for negative data, thus providing a static effect during training to solve the dead ReLU phenomenon and overcome the over fitting problem.

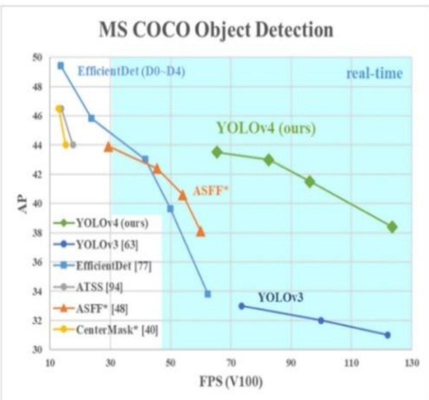
3.) CSP DarkNet53:-

YOLOv4 uses CSPDarknet53 as its discovery architecture. **CSPResNext50** is better at classifying objects inILSVRC20212(ImageNet), while **CSPDarknet53** is better at recognizing objects in MS COCO dataset.The operating diagram of the original YOLOv4 is shown in Figure b, charts comparing base performance, fps and AP to other methods.

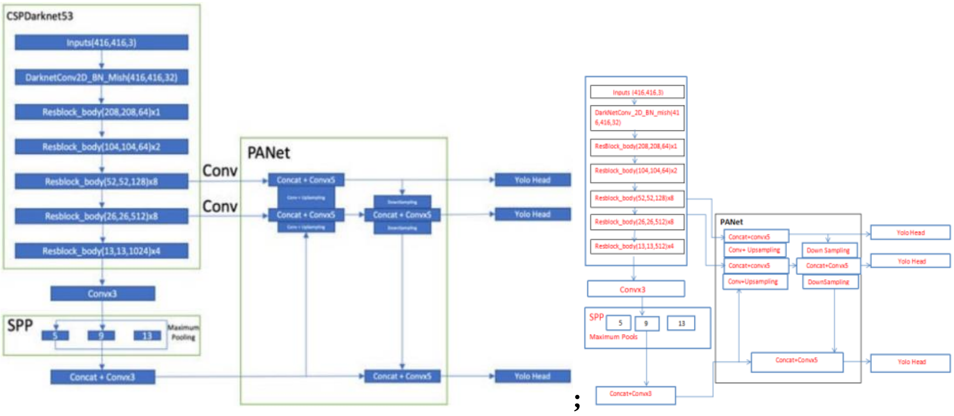
YOLOv4's performance is shown in green, labeled "YOLOv4".YOLOv3's FPN has been replaced with PA-Net as an integrated method in YOLOv4.
The ultimate YOLO head is based on the YOLOv3concept. In short, the YOLO head works in three steps. First, it divides the entire image into N×N grid s. Each grid has five parameters (eg. x, y, w, h, and c; object_con-fidence_score), where (x, y) is the offset of the axis and the boundary of the link, (w, h) is the approximate width and height of the entire image, object_confidence_score represents the object in the class. CNNs extract features and predict classes with class scores.
The yolov4 detection architecture is shown in figure (c).



(a) comparison of Mish activation with RelU, SoftPlus and Swish:-



(b) Comparison of Yolov4 (original) with other object detectors



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(c)Yolov4 Detection Architecture

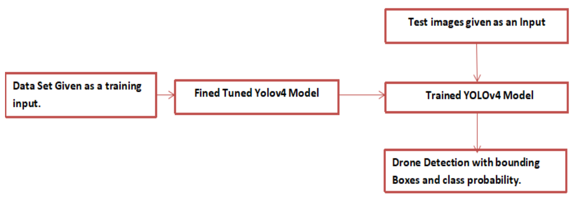
II. Results:-

Construction of Experiment:-

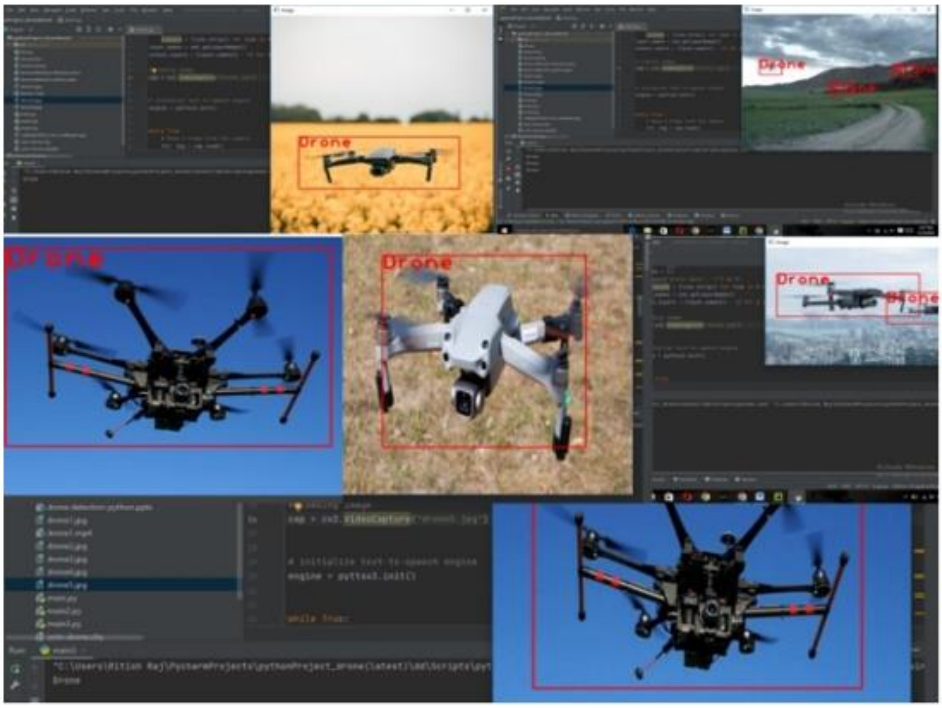
DJI Phantom III and Mavic Pro drone types were utilised. To evaluate the YOLOv4 training's detection speed and capabilities, the drone was flown at three different elevations. We picked this height since the drone would be virtually undetectable on camera over 60 feet. main code for the Darknet framework were wriiten and in our research we used the learning pass to align the framework with our private data.We are ending our YOLO,convolution techniques for private lesson.

The original darknet was trained with 80 classes,we change the class to a "drone" so we can handle all the lo ad on the GPU. Before the three YOLO layers, there are three convolutional layers for creating high-level feature maps of objects. In the convolution process, filters are used to extract features. We turn on th e MOSAIC flag to automate the data augmentation process. We set the batch number and set it to 64. Depending on the GPU, there are many numbers to try for subdivisions, starting with 8 and using the model in multiples of 8 Steps (80% and 90% of the largest elements).Finally,we trained YOLOv4 on Google's Deep Lear ning Virtual Machine and then tested it on our test images and videos. We train **YOLOv4** for 4000 iterations and record the trainingweights for every 1000 iterations, then buildmultiple iterati ons against multiple iterationsmAP curve Weight net frame at four different points based on default Dark record ed at 1000, 2000, 3000 and 4000 iterations.The flow chart of the whole experiment is shown in figure (d).

(d)Diagram of the Experiment



(d) Flow Chart of the Experiment



III. Conclusion:-

We chose this altitude because above 60 feet the drone would appear almost invisible on camera.

We wrote the main code for the Darknet framework and in our research ,we used the learning pass to align the framework with our private data. We are ending our YOLO and convolution techniques for private lessons.

The original darknet was trained with 80 classes, so we change the class to a "drone" so we can handle all the load on the GPU. Before the three YOLO layers, there are three convolutional layers for creating high-level feature maps of objects. In the convolution process, we use filters to extract features. We turn on the MOSAIC flag to automate the data augmentation process. We set the batch number and set it to 64.Depending on the GPU, there are many numbers to try for subdivisions, starting with 8 and using the model in multiples of 8 Steps (80% and 90% of the largest elements). Finally, we trained YOLOv4 on Google's Deep Learning Virtual Machine and then tested it on our test images and videos. We train YOLOv4 for 4000 iterations and record the training weights for every 1000 iterations, then build multiple iterations against multiple iterations. mAP curve Weight net frame at four different points based on default Dark recorded at 1000, 2000, 3000 and 4000 iterations. The flow chart of the whole experiment is shown in figure (d). used or the hardware used must be top notch for better result also the camera resolutions should be high as much as possible.

Abbreviations:-

CNN	Convolution Neural Networks
COCO	Common object in context
GPU	Graphical Processing Unit
CSP-Net	Cross-Stage Partial Network
FLOPS	Floating Point Operations Per Seconds
FPS	Frames Per Second
Google Colab	Google Colaboratory
IoU	Intersection-Over-Union
KNN	K-nearest-neighbor
Lr	learning- rate
mAP	Mean-Average-Precision
R-CNN	Region-Based Convolution-Neural Network

UAVs	Unmanned-Arial-Vehicles
VM	Virtual-Machine
YOLO	You-Only- Look Once
YOLOv2	You-Only-Look-Once-version 2
YOLOv3	You-Only-Look-Once-version 3
YOLOv4	You-Only-Look-Once-version 4

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