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DRONE DETECTION USING DEEP LEARNING

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ABSTRACT

Drones have widespread application in real life and the industry is expanding rapidly. As they are growing increasingly it is more accessible to the public at cheaper prices. They are used for espionage and can be converted into gruesome weapons. Hence it is very important to monitor and detect unauthorized drones entering into the restricted regions in order to maintain peace and prevent chaos. The Technology stack implied here is You Only Look Once (YOLO v5) which is a real time object detection system. In recent times Yolo is a profound algorithm used for real time object or image detection . The Yolo trained model is trained with pictures of drones and birds so that the trained model can differentiate between and prevent false prediction of drones . Everytime a drone is detected in the camera an alert message is sent to the higher officials so that the drone could be eliminated. This algorithm comprises 3 techniques namely: Residual blocks, Bounding box regression and Intersection over Union. The camera used here is 360 degree so that maximum area of visibility is obtained.

KEYWORDS: ***Drones, real time object detection , YOLO v4.***

I. INTRODUCTION

Drones have many real time uses like surveillance , detection, delivery in day to day life. As all the technological development can be exploited to use it for malicious intentions , drones can also be used in trafficking drugs , transporting the weapons and goods between borders. The main aim of our idea is to detect drones using the YOLO algorithm and alert the respective officials using Twilio API. YOLO uses neural networks to provide real-time object detection. This algorithm is popular because of its speed and accuracy. There is an increasing potential for small drones to be misused, especially by hobbyists, as well as for illegal activities such as drug smuggling, terrorist attacks, or even interfering in emergency services such as fire prevention and disaster response. The collection of drone images ,the labeling process is done and the dataset is trained. The live video feed is passed to the developed framework, thereby detecting the drones in the feed. When a drone is captured, our proposed system will detect them and notify the officials by sending sms(Twilio API). Twilio is a Cloud communications Platform as a Service company that, among many other features, offers an API that allows to programmatically send SMS.

II. EXISTING WORK

There exists a system which uses CNN-based network architectures such as Zeiler and Fergus (ZF) and the Visual Geometry Group (VGG16) to transfer learning and to detect drones. Their results showed that VGG16 with Faster R-CNN performed better than other architectures did on a training dataset containing five MPEG4-codec videos taken at different times. Another system proposed an audio-based drone detection technique using CNN, a recurrent neural network, convolutional

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recurrent neural network algorithms, and the unique acoustic fingerprints of flying drones. Their dataset consisted of audio recorded samples of drone activities.Their dataset contained more than 10,000 images of different categories of drones. An OpenCV-based drone detection system was proposed, achieving 89% accuracy. A dataset contained 2088 positive and 3019 negative examples, used YOLOv3 to achieve better detection accuracy and obtained more accurate bounding boxes.

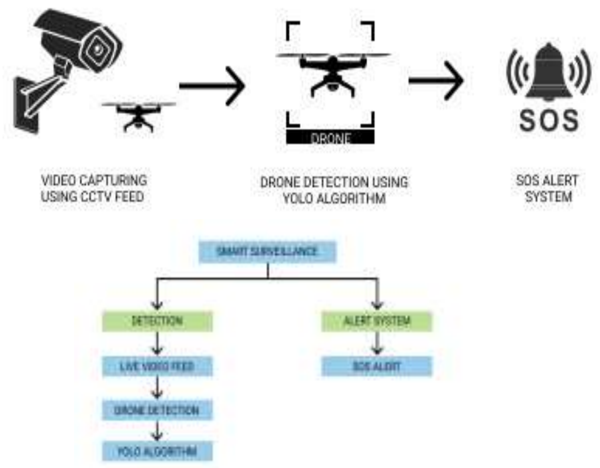
III. PROPOSED SYSTEM

The proposed solution has three parts , capturing the video in real time using the 360 degree CCTV , detecting the drone in the video using the trained model. In this study, we have chosen to use the state-of-the-art in object detection, the YOLO-v4 algorithm, because of its real-time detection capabilities, high speed, and accuracy. To train this neural network architecture, we collected images of birds as well as drones from public resources. We prepared our own drone dataset to verify the drone detection capability. We chose to use bird images due to their similarity to drones. We used mean average precision (MAP) as our evaluation metric to evaluate the object detector's performance. Using the collected and prepared dataset, the trained YOLOv4 neural network was evaluated in terms of its detection ability, location precision, and mAP. YOLOv4 follows a one-stage detector architecture consisting of four parts: input, backbone, neck, and dense prediction or head. The input is the set of data we want to detect. The backbone is responsible for extracting features and uses the image dataset to make the object detector scalable and robust.

Bag of Specials

YOLOv4 introduces a set of strategies called BoS to improve object detection accuracy by increasing a small amount of inference costs. Various techniques are incorporated in order to implement BoS, but the most significant improvements include Mish activation, CSP connections, SPP-block, and PAN path-aggregation block. Mish activation considers the negative information, thus solving the dying ReLU phenomenon and providing strong regularization effects during training to overcome the overfitting issue.

The trained YOLOv4 was evaluated using mAP, precision, recall, and F1-score.Primarily, an evaluation was performed for the testing images of birds and drones. In addition, our testing was performed considering a complex background, different weather conditions (cloudy, sunset, etc.), and multiple objects in one image. After the collection of drone images ,the labeling process is done and the dataset is trained. The live video feed is passed to the developed framework, thereby detecting the drones in the feed. When a drone is captured, our proposed system will detect them and notify the officials by sending sms(Twilio API).



V. RESULT AND CONCLUSION

In this research, YOLOv4 was trained to detect drones. Our model performed better than those of previous similar studies. Drone detection is necessary, considering that drone intervention is frequent in unauthorized and emergency tasks. However, detecting drones at various altitudes can be difficult, especially due to their small size and high altitude and speed as well as the existence of drone-like objects. Drone and bird image databases were compiled in this research by collecting images from available public resources. Using those collected images, a YOLOv4 model was trained and evaluated via our own drone videos.This study was limited to YOLO implementation only since various object detection algorithms require datasets to be labeled in certain formats, which is time consuming. In addition, speed was one of our considerations while choosing algorithms. In future work, a more diverse image dataset will be used to further improve the results. Thus, we will further use this version to see if the speed and accuracy improve. In this study, YOLOv4 performed better due to the capability of detecting objects in real-time. The YOLO algorithm predicts a class with localization using only a single pass over an image. In this study, YOLOv4 performed better due to the capability of detecting objects in real-time. The YOLO algorithm predicts a class with localization using only a single pass over an image.

VI. FUTURE SCOPE

In future drone detection will be used to prevent illegal use of drones in order to prevent security breaches and to ensure public safety. The drone industry is expanding rapidly. They are growing increasingly more accessible to the public and at cheaper prices . According to their payload capability, drones can be used for various purposes, such as inspection, delivery, monitoring, photography, and among other uses. However, drones can also be misused, generating safety concerns. There is an increasing potential for small drones to be misused, especially by hobbyists, as well as for illegal activities such as drug smuggling, terrorist attacks, or even interfering in emergency services such as fire prevention and disaster response. Drones can also be converted into dangerous weapons by loading them with explosive materials. However, they are not easy to detect when in the air. Small drones transmit very limited electromagnetic signals, making it very difficult for conventional radar to detect them. Conversely, object detection using deep learning has achieved substantial success due to its high accuracy and available computing power . In fact, the "You Only Look Once" (YOLO) algorithm has surpassed other object detection algorithms such as the Region-Based Convolutional Neural Network (R-CNN) and the Single-Shot Multibox Detector (SSD) because of its highly precise real time detection capability . YOLO is superior in terms of both accuracy and speed.

VII. REFERENCES

1. *Behera, D.K.; Raj, A.B. Drone Detection and Classification Using Deep Learning. Proceedings of the 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 13–15 May 2020; IEEE: Piscataway Township, NJ, USA; pp. 1012–1016.*
2. *Seidaliyeva, U.; Alduraibi, M.; Ilipbayeva, L.; Almagambetov, A. Detection of Loaded and Unloaded UAV Using Deep Neural Network. In Proceedings of the 2020 Fourth IEEE International Conference on Robotic Computing (IRC), Taichung, Taiwan, 9–11 November 2020; pp. 490–494.*
   Rohan, A.; Rabah, M.; Kim, S.-H. Convolutional Neural Network-Based Real-Time Object Detection and Tracking for Parrot AR Drone 2. IEEE Access 2019, 7, 69575–69584
3. *Albawi, S.; Mohammed, T.A.; Al-Zawi, S. Understanding of a Convolutional Neural Network. In Proceedings of the 2017 International Conference on Engineering and Technology (ICET), Antalya, Turkey, 21–23 August 2017; pp. 1–6.*
4. *Hu, Y.; Wu, X.; Zheng, G.; Liu, X. Object Detection of UAV for Anti-UAV Based on Improved YOLO V3. In Proceedings of the 2019 Chinese Control Conference (CCC), Guangzhou, China, 27–30 July 2019; pp. 8386–8390.*
5. *Girshick, R. Fast R-CNN. In Proceedings of the 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, Chile, 7–13 December 2015; pp. 1440–1448.*
6. *Ren, S.; He, K.; Girshick, R.; Sun, J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Trans. Pattern Anal. Mach. Intell. 2017, 39, 1137–1149.*
7. *Mahdavi, F.; Rajabi, R. Drone Detection Using Convolutional Neural Networks. In Proceedings of the 2020 6th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), Mashhad, Iran, 23–24 December 2020; pp. 1–5.*
8. *Coluccia, A.; Fascista, A.; Schumann, A.; Sommer, L.; Ghenescu, M.; Piatrik, T.; De Cubber, G.; Nalamati, M.; Kapoor, A.; Saqib, M.; et al. Drone-vs-Bird Detection Challenge at IEEE AVSS2019. In Proceedings of the 2019 16th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), Taipei, Taiwan, 18–21 September 2019; pp. 1–7.*
9. *Aker, C.; Kalkan, S. Using Deep Networks for Drone Detection. In Proceedings of the 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), Lecce, Italy, 29 August–1 September 2017*