ISSN No:-2456-2165

Drone Movement Detection Network using Raspberry Pi

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Abstract:- This research paper proposes a system for detecting drones that use Raspberry Pi as its primary computing platform and implements the SSD MobileNetv2 architecture. The proposed approach involves training a machine learning model using deep learning and convolutional neural network algorithms. The SSD Mobilenetv2 architecture is proposed due to its accuracy and optimal performance in real-time object detection. The dataset includes images of numerous drones in various positions. The dataset has undergone image augmentations such as flipping, blurring, granulation and grayscale conversion, at random, before training. Multiple cameras, connected over a network, are connected to a Raspberry Pi employing star network topology with Raspberry Pi as the central hub. A dedicated machine, with the machine learning model running on it, accesses the video feeds from raspberry pi and infers them in real-time. The detection results are sent to the raspberry pi. Computer vision techniques are applied to the region of interest in the video feeds to determine the drone's trajectory. The system includes physical and digital alerts comprising alarm systems and SMS alerts so that authorities can be informed immediately whenever a drone is detected.

***Keywords**:- Drones, Raspberry Pi, SSD MobileNetv2, real-time detection, star network topology, trajectory,SMS alerts*

I. INTRODUCTION

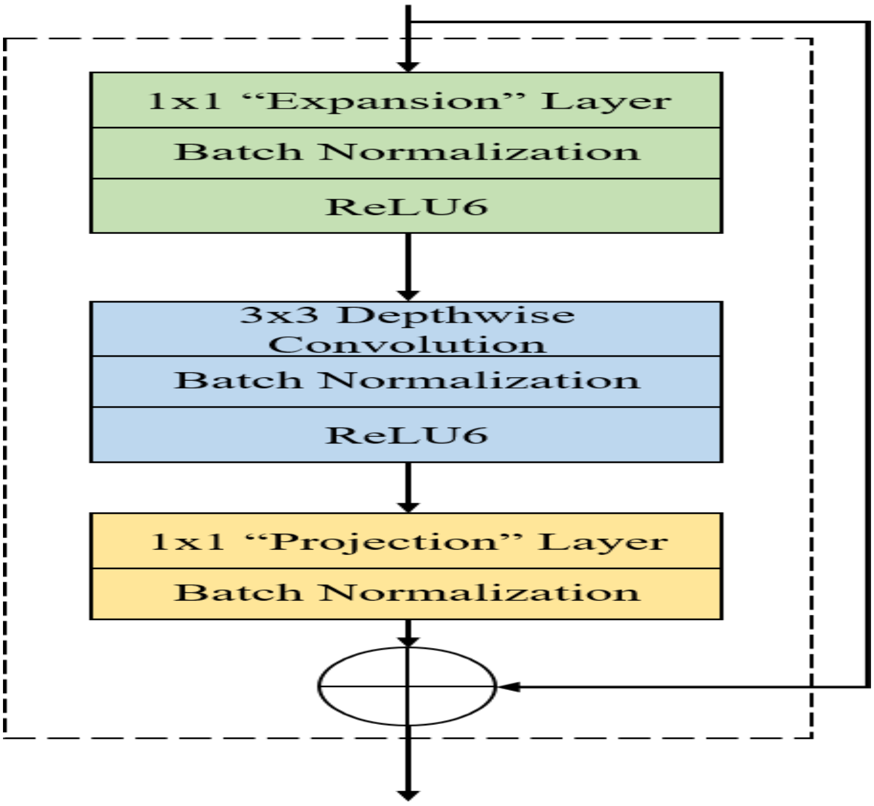

Fig. 1: Bottle Neck Residual Block of MobileNetv2

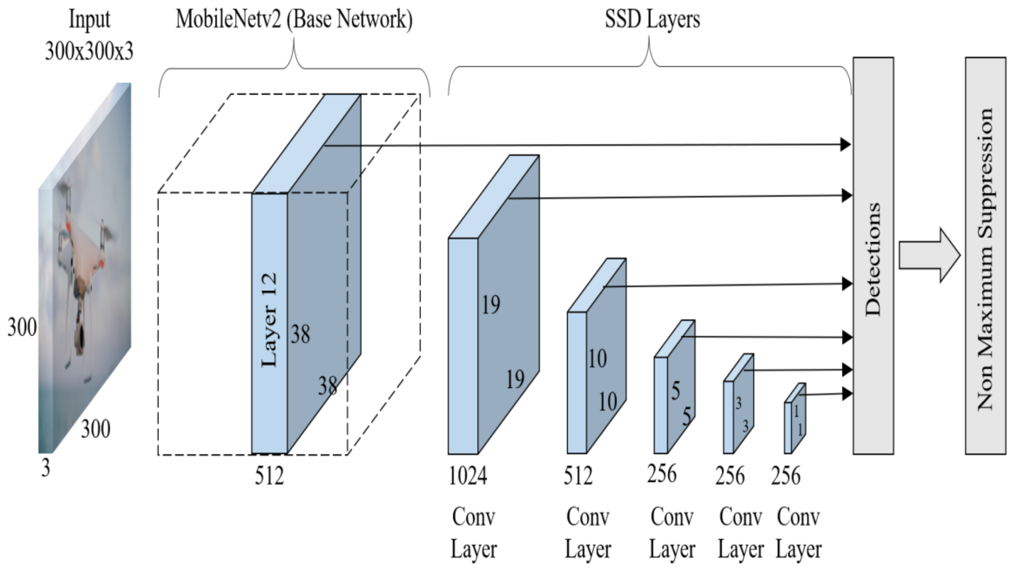

Fig. 2: SSD Mobile Netv2 Architecture

Drones have become increasingly popular in recent years, due to their usability and numerous applications suitable for variety of fields. Drones have been integrated into various fields such as, agriculture [1], search and rescue [2] operations, aerial photography, forest fire detection [3], smoke detection [4], delivery services and many more. Drones are capable of performing inspection and mapping of topology of various terrains [5], geological surveys [6] more efficient than humans. They are used in situations where human intervention is hazardous such as, inspection of volcanoes, inspection of oil rigs and power plants etc. However, drones also pose a significant threat. As they are small and compact, they can perform damaging activities while being hidden. Drones can be used to fly over restricted areas such as airports and government buildings and may acquire sensitive information. They can capture videos and images without the consent and acknowledgement. Drones can also be an application for illegal surveillance and smuggling, which can cause irreparable damage to individuals, organizations and countries. Terrorists have been using drones for spying and obtaining sensitive information, leaking confidential information and attacking public places and military bases.Machine learning algorithms have become robust and can perform efficiently under critical conditions. TensorFlow is a framework used to train advanced machine learning models. TensorFlow has an Object Detection API for training object detection and classification models. It has various models pre-trained on different algorithms such as CenterNet,EfficientDet, SSD MobileNet, SSD Resnet, Faster-RCNN and Mask-RCNN. TensorFlow models require less computational resources and can perform with speed and accuracy. Due to its requirement for fewer resources, devices like embedded hardware and single-board computers can make use of TensorFlow models. SSD MobileNetv2 is such an architecture.The MobileNetv2 contains three convolutional layers[7]. The Expansion layer's function is to expand the number of channels in the input tensors, before Depthwise convolution is applied. The Depthwise convolution layer performs a 3x3 depthwise channel filtering operations. The Projection layer performs reduction of the number of tensor channels and dimensions.

The MobileNetv2 is used as a base for the SSD architecture.The Single Shot Detector (SSD) is used for detection and classification. The SSD architecture is built upon a MobileNetv2 base, but the fully connected layers of MobileNetv2 are discarded. This enables the model to run on devices with low resources and perform at optimum speed[8]. The SSD performs object localization and classification in a single task. The Non-Maximum Suppression (NMS) is performed by using the bounding box regression technique Multibox[9]. Multibox uses Inceptive convolutional network[10]. The loss function of Multibox is comprised of location loss and confidence loss. The Multibox Intersection over Union (IOU) uses priors as prediction results and regresses them attempting for a closer ground truth bounding boxes, resulting in non-maximum suppression.

II. CREATING THE MODEL

A. Dataset

The dataset contains 4032 images of drones. Region of interest in each image is annotated. The annotations are saved in ".xml" format. The images and their respective annotations are divided into three parts before applying dataaugmentation techniques. The train dataset contains 3024 images, the test dataset contains 806 images and the valid dataset contains 202 images. The training dataset is pre-processed by applying gaussian blur, grayscale conversion, flip and granulation at random. The image augmentations are also applied to test dataset. The accuracy and false positive rate greatly depend on the quality of the data set. The data augmentation process ensures the training data to be reliable and results in a model with higher degree of accuracy and lower false positive rate [11].

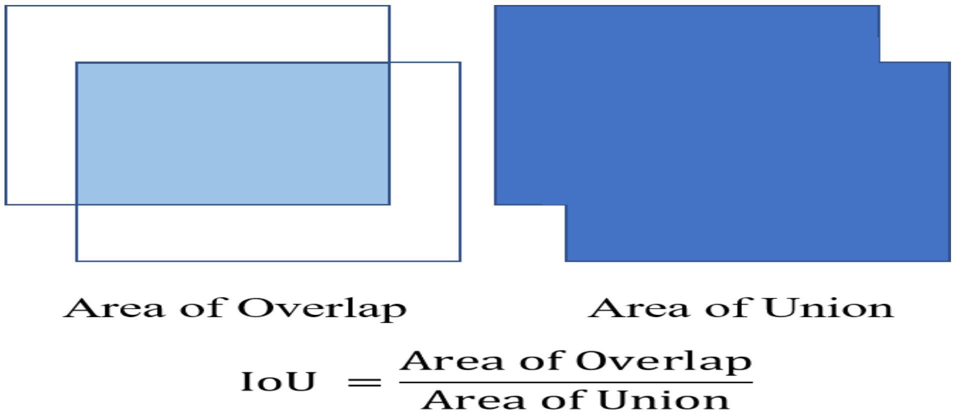

Fig. 3: Intersection over Union calculation

B. Training

The annotations are converted into a TensorFlow record format. A label map containing one object id is created. The SSD MobileNetv2 architecture is configured and fine-tuned to the obtained TensorFlow records. The configuration is defined for a single class, with a batch size of 8 and number of steps of 2000. The lower batch size enables the model to work with lower resources, the number of steps define the number of iterations for weights updating in every epoch of training. The model accuracy and performance are greatly influenced by the regularization techniques, which also prevents overfitting. The SSD MobileNetv2 architecture uses Weight decay, Dropout, batch normalization and data augmentation techniques. Data augmentation is directly performed on the dataset beforetraining. Weight decay adds a penalty term to the loss function. This makes the model adapt to smaller weights, improving reliability. Dropout randomly drops some of the neural network units by setting them to zero. This forces the model to adapt and be more robust. The model is trained until a constant loss is achieved. Each epoch is saved as a checkpoint. The trained weights are stored in a protocol buffer format. These weights are frozen by converting them into a Graph Definition, essentially combining the trained weights and meta data. The frozen weights and the configuration pipeline collectively represent the trained model. The weights are inferred on both test and valid datasets.

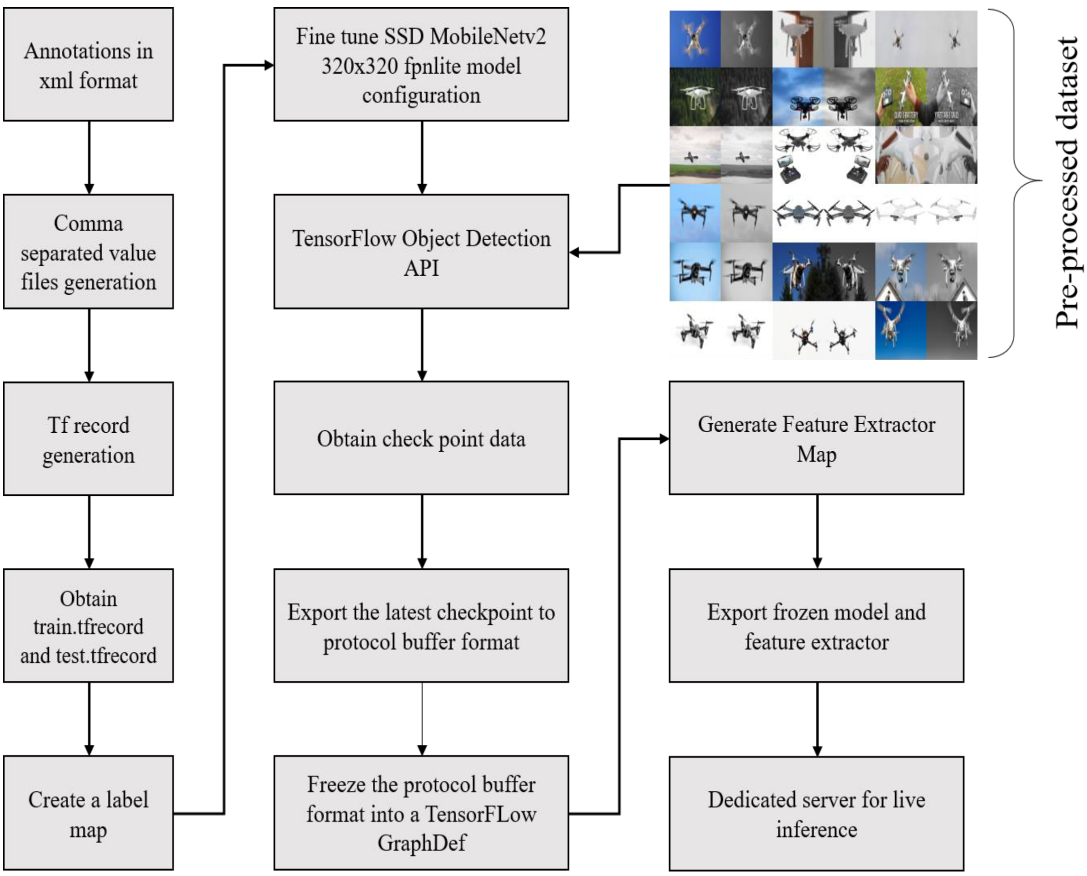

Fig. 4: Process of creating the model

ISSN No:-2456-2165

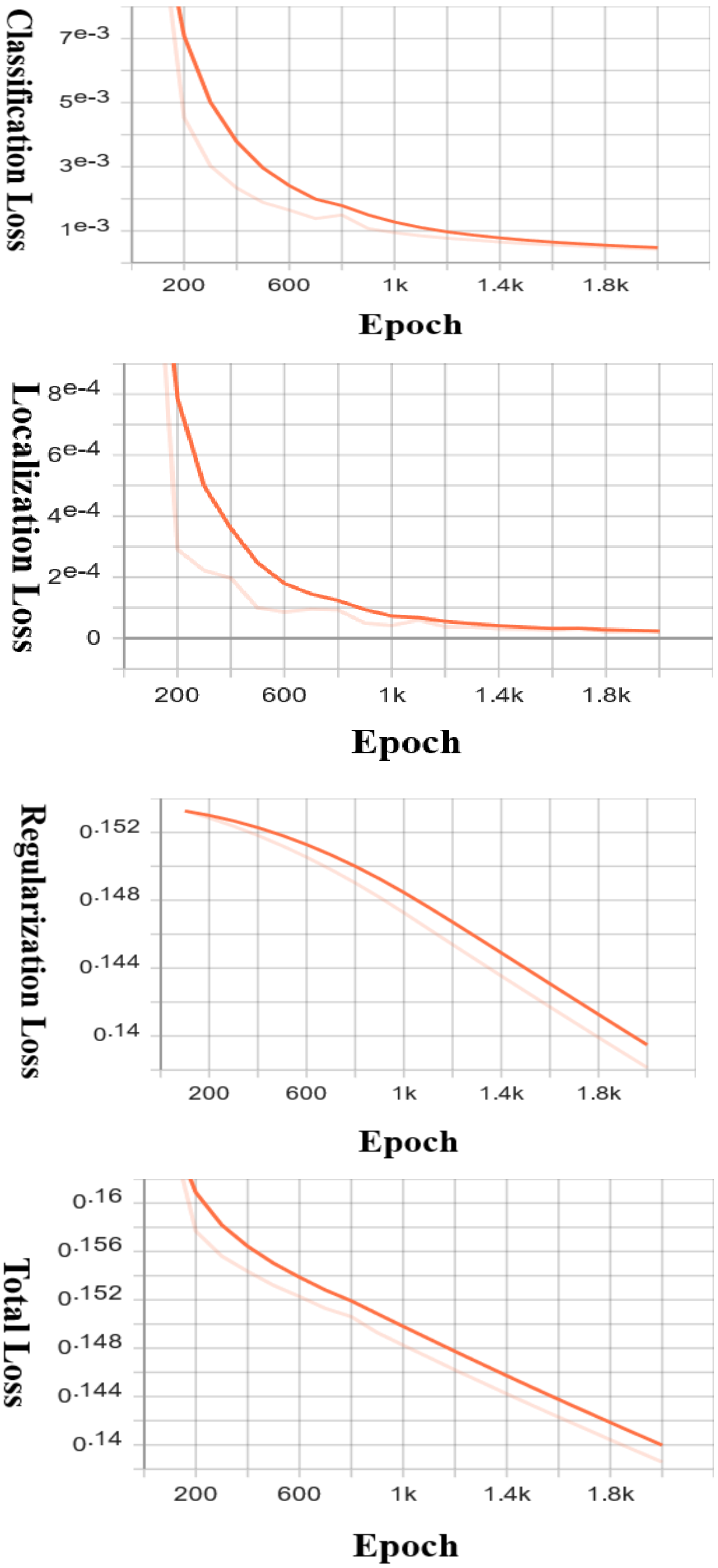

Fig. 5: Losses obtained during training

ISSN No:-2456-2165

III. DRONE DETECTION SYSTEM

The proposed system consists of camera network, a raspberry pi, a physical alarm system, an SMS API and an application for remote access. The camera network consists of multiple cameras connected over a Wide Area Network. The access point for all these cameras is the raspberry pi. The raspberry pi is configured to act as a hub for the cameras. The raspberry pi has two internal systems, a video server and a trajectory determining system.

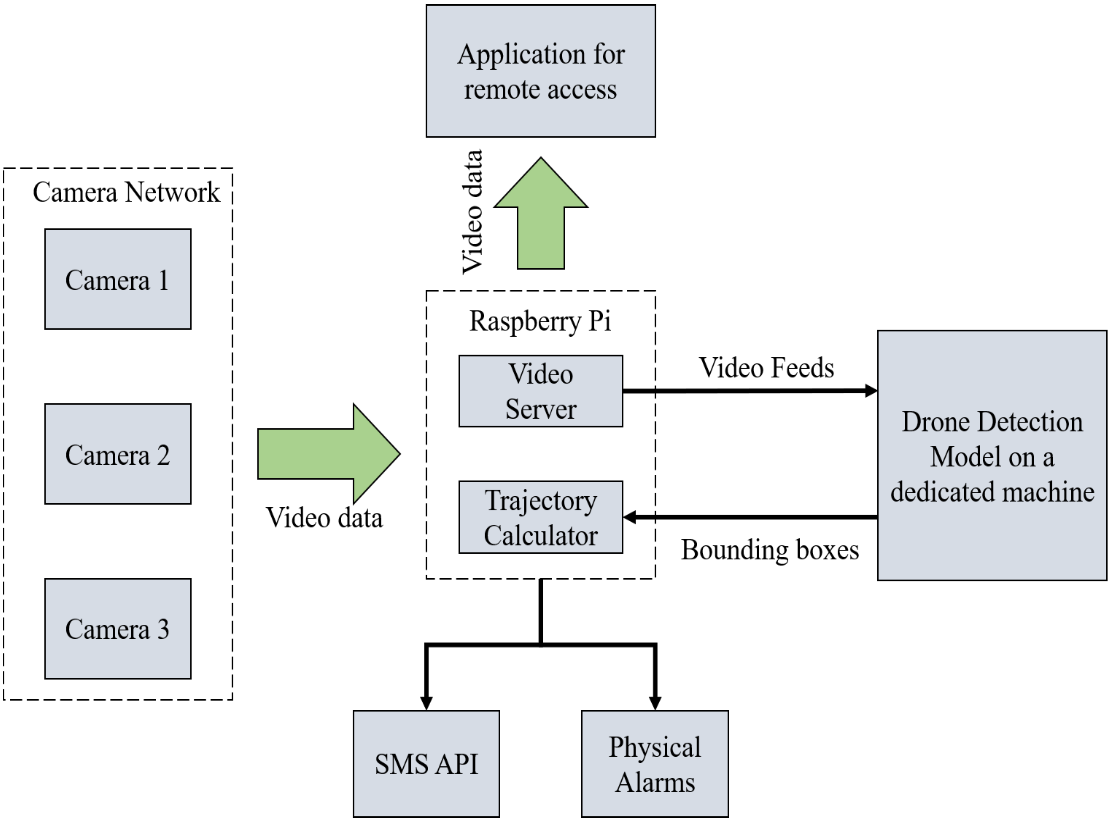

Fig. 6: The proposed system

The video server uses RTSP protocol [12] for accessing the camera video feeds and FFMPEG protocol [13] for relaying the video feeds to the machine learning model. The dedicated machine runs an inference script, which uses multithreading and thread-pooling for the incoming video feeds. Each thread accesses the model individually and sends the detection results, which comprises of confidence scores, class names and bounding boxes, to the raspberry pi. The detection results are given to the trajectory determining system in the raspberry pi. The trajectory determining system creates its own region of interest based on the bounding boxes. These regions of interest will undergo a motion detection algorithm [14], which involves applying the absolute difference between two subsequent video frames as a threshold mask to the regions of interest. A binary version of the absolute difference mask is used for detecting contours whenever the subsequent frames differ. The shift in the centroid of the contour in respective frames determines the drone trajectory. The physical alarm systems are triggered by the detection results. The SMS API sends an alert message periodically to the users. The video feeds can be accessed remotely on the network through a flask application.

IV. RESULTS

The output of the detection system is accessible through the application. The system was tested using three cameras, a WIFI camera, a web camera and an USB camera. The app displays the detection results of these cameras in three cells. A fourth cell is used to display the trajectory and location information of the detected drone. The location information is based on the location of the camera.

V. CONCLUSION

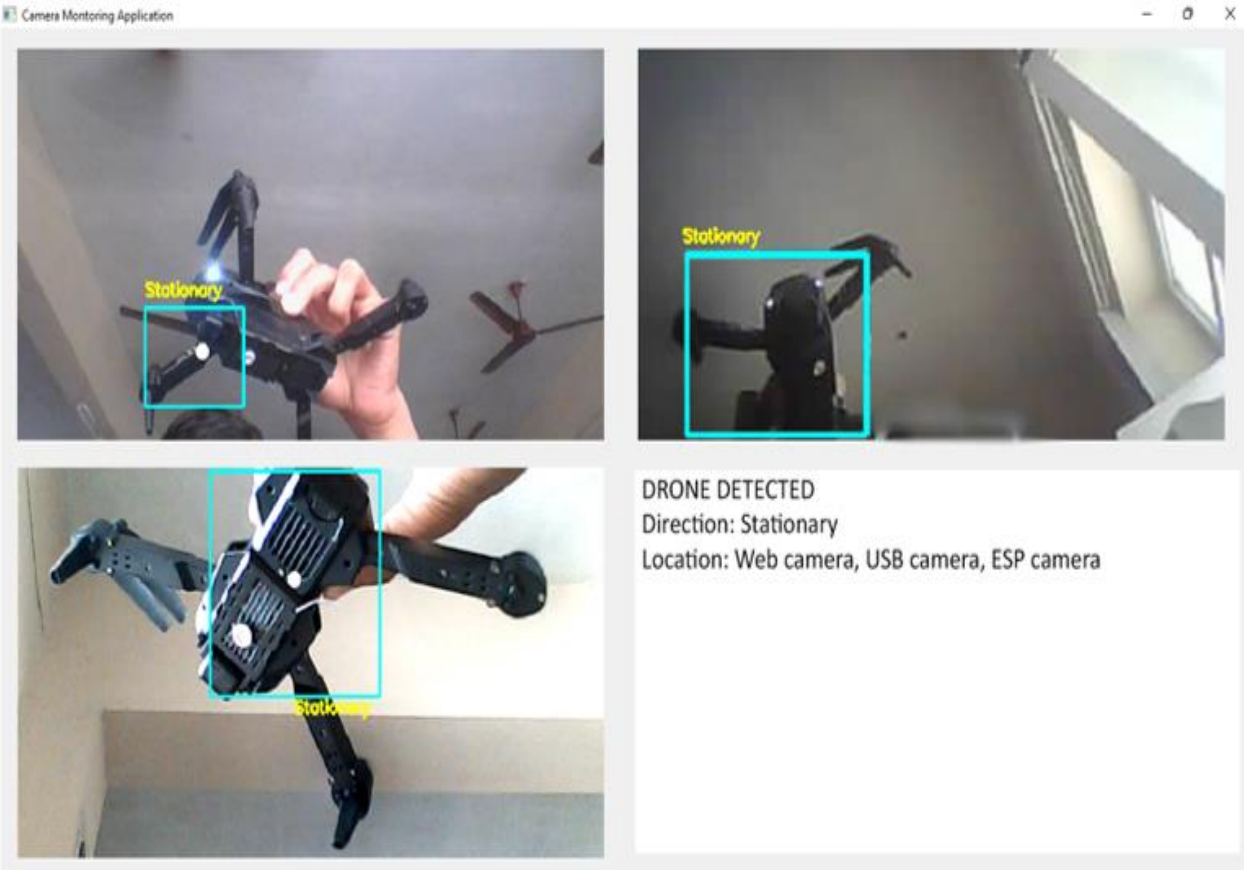

Fig. 7: The output of the proposed system

This study outlined the usage of machine learning models on low resource devices with optimal real-time performance. The proposed system is a low-cost security deviceintegrated with machine learning, with a wide range of coverage, which is both reliable and efficient for operating in real-time. The application for monitoring camera feeds and the SMS alerts makes the system reliable in situations where time is critical.

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