OBJECT TRACKING USING DRONE FOR SMART AGRICULTURE

A BTP Report

By

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INDIAN INSTITUTE OF INFORMATION TECHNOLOGY SRI CITY

Date 20/12/2022

Final Report

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY SRI CITY

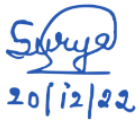
CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the BTP entitled "**OBJECT TRACKING USING DRONE FOR SMART AGRICULTURE**" in the partial fulfillment of the requirements for the award of the degree of B. Tech and submitted in the Indian Institute of Information Technology SriCity, is an authentic record of my own work carried out during the time period from January 2022 to December 2022 under the supervision of Dr. Y Raja Vara Prasad, Indian Institute of Information Technology Sri City, India.

I have not submitted the matter presented in this report for the award of any other degree of this or any other institute.

Signature of the student with date

Kamarthi Litheesh Kumar, 20/12/2022



TU Surya Sathvik, 20/12/2022

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Signature of BTP Supervisor with date

Dr. Y Raja Vara Prasad

ABSTRACT

Owing to effective and flexible data acquisition, unmanned aerial vehicle (UAV) has recently become a hotspot across the fields of computer vision (CV) and remote sensing (RS). Inspired by the recent success of deep learning (DL), many advanced object detection and tracking approaches have been widely applied to various UAV-related tasks, such as environmental monitoring, precision agriculture, and traffic management. This project provides a comprehensive survey of the research progress and prospects of DL-based UAV object detection and tracking methods. More specifically, we first outline the challenges, and statistics of existing methods, and provide solutions from the perspectives of DL-based models in three research topics: object detection from the image, object detection from the video, and object tracking from the video.

Open datasets related to UAV-dominated object detection and tracking are exhausted, and four benchmark datasets are employed for performance evaluation using some state-of-the-art methods. Finally, prospects and considerations for future work are discussed and summarized. It is expected that this project can facilitate those researchers who come from the remote sensing field with an overview of DL-based UAV object detection and tracking methods, along with some thoughts on their further developments.

Purpose: Computer vision in drones has gained a lot of attention from artificial intelligence researchers. Providing intelligence to drones will resolve many real-time problems. Computer vision tasks such as object detection, object tracking, and object counting are significant tasks for monitoring specified environments.

Methodology: In this project, a detailed literature review has been conducted focusing on object detection and tracking using UAVs concerning different applications. This study summarizes the findings of existing research papers and identifies the research gaps.

Contribution: Object detection methods applied in UAV images are classified and elaborated. UAV datasets specific to object detection tasks are listed. Existing research works in different applications are summarized. Finally, a secure onboard processing system on a robust object detection framework in precision agriculture is proposed to mitigate identified research gaps.

Index Terms - Object detection, object tracking, remote sensing, unmanned aerial vehicle, video.

Contents

1. INTRODUCTION.

Object detection and tracking, as an important research topic in the field of remote sensing, has been widely investigated and applied to various civil and military tasks, such as environmental monitoring, geological hazard detection, precision agriculture, and urban planning. Traditional object acquisition methods derive mainly from satellites and manned aircraft. Normally, the two types of platforms run on a fixed rail or follow a predetermined path, or temporarily change the running route and hover according to a commissioned task, e.g., city planning and mapping, or performing object observation in a harsh and inhospitable environment.

However, the cost of satellites and manned aircraft, and the potential safety issues of pilots inevitably limit the application scope of such platforms. With the development of microelectronic software and hardware, navigation and communication technology renewal, and breakthroughs in materials and energy technology, the unmanned aerial vehicle (UAV) platform already an international research hotspot in remote sensing has rapidly emerged. A UAV remote sensing system is a high-tech combination of science and technology integrated UAVs, remote sensing, global positioning system (GPS) positioning, and inertial measurement unit (IMU) attitude determination means. It is a dedicated remote sensing system with the goal of obtaining low-altitude high-resolution remote sensing images. Compared with traditional platforms, UAVs make up for information loss caused by weather, time, and other limitations.

Computer vision is already achieved remarkable achievements due to advancements in deep learning algorithms, hardware requirements, and the availability of datasets. Object detection is the most investigation task done by researchers as it has many applications. The objective of object detection is to detect objects from a certain category (for example human beings, dogs, vehicles, motorcycles, or cats) in a picture and if any, return the area and extent of each instance of objects. It constitutes the backbone for solving complex and high-level computer vision tasks such as object tracking, segmentation, event detection, image captioning, scene comprehension, crowd monitoring, and activity recognition. Researchers started to overcome the challenge of developing general object detection systems that can detect categories of objects which match human ones. The field of object detection has been greatly enhanced. However, object detection in drone applications is yet to research. From surveillance to agriculture, all applications need accurate object detection to serve their purpose.

Precision agriculture is expected to see significant growth compared to other applications, as the use of UAVs is becoming one of the most crucial parts of managing farm tasks. Precision agriculture is a collection of methods for tracking crops, collecting data, and carrying out informed crop management tasks such as the optimal water supply, and the selection of effective pesticides. UAVs can assist farmers in a vast range of activities such as planning and analyzing crop plantation, and farm monitoring to assess crop growth and health. The benefits of using aerial services in agriculture favored the expansion of the use of fertilizers from the air in 1940 to other activities, such as top dressing. A drone manufacturing company called DJI developed drones by integrating sensors especially for protecting crops from insects or weeds.

Although drones are popular now, their history is long years back. It can be categorized based on flying speed, stabilizing its position, hovering, fixed or loitering, and flying environment. Different types of UAVs have different characteristics. Single-rotor UAVs can carry heavy payloads but it has mechanical complexity which leads to high cost. Multirotor UAV is a common type as its usage applies to both professionals and common people. It can hover or move along the given target.

However, changes in viewpoint and changes in scale make the object detection task in drones more challenging than traditional object detection. In a traffic surveillance scenario, drones record traffic from a bird's eye view. The advantage of this to 100 m in height to record vehicle traffic. Object detection from a bird's eye perspective is more challenging than the front-parallel view for the following aspects,

- The dynamic transition of moving objects.
- Changes in aspect ratio and image scale.
- Abrupt camera motion.
- Severe perspective distortion.
- Motion blur.
- The high density of objects.
- Complex background.

In addition to these difficulties, object detection studies in aerial view are also confronted by the biased dataset problem. To avoid this problem, the dataset must be annotated which reflects real-world applications. Therefore, it is not unusual that the object detection models learned from traditional images are not appropriate for aerial images.

2. LITERATURE SURVEY

2.1. Small-Object Detection Algorithm:

Most state-of-the-art detectors are based on deep-learning methods. These methods mainly include two-stage detectors, one-stage detectors, and anchor-free detectors. Two-stage detectors first extract possible object locations and then perform classification and relocation. The classic two-stage detectors include spatial pyramid pooling networks (SPPNet), faster region-CNN (RCNN), etc. The one-stage detectors perform classification and positioning at the same time. Some effective one-stage detectors mainly include the single-shot multi-box detector (SSD), You Only Look Once (YOLO) series, etc. Anchor-free detectors include CenterNet, ExtremeNet, etc. These methods do not rely on predefined anchors to detect objects. In addition, some scholars have introduced transformers into the object detection field, such as detection with transformers (DETR) and vision transformer faster RCNN (ViT FRCNN), which have also achieved good results.

However, the detection objects of the general object detectors are multi-scale. They are not designed for small-object detection specifically. Small-object detection algorithms can be mainly divided into two kinds. One is to improve the detection performance of small objects with multiple scales in a video or image sequence. The other is to improve the detection performance of small objects with only a scale in an image. The improved detection methods of small objects with multiple scales mainly include feature pyramids, data augmentation, and changing training strategies.

In 2017, Lin et al. proposed feature pyramid networks (FPN), which improve the detection performance effect of small objects by fusing high-level and low-level features to generate multi-scale feature layers. In 2019, M. Kisantal et al. proposed two data augmentation methods for small objects to increase the frequency of small objects in training images. B. Singh et al. designed scale normalization for image pyramids (SNIP). SNIP selectively backpropagates the gradients of objects of different sizes, and trains and tests images of different resolutions, respectively.

The research object of Drones 2022, 6, 308 3 of 19 these methods is multi-scale objects, which cannot make full use of the characteristics of small objects. The approaches that only detect small objects with a scale are mainly of three kinds: designing networks, using context information, and generating super-resolution images. L. Sommer et al. proposed a very shallow network for detecting objects in aerial images. Small-object detection based on network design is few and immature. J. Li et al. proposed a new perceptual GAN network to improve the resolution of small objects to improve detection performance. In this paper, we focus on algorithms that are suitable for small-object detection in UAV reconnaissance images.

2.2. Object Detection Algorithm for UAV:

The object detection algorithms used in UAVs are mainly designed based on the requirements of the task scenarios. M. Liu et al. proposed an improved detection algorithm based on YOLOv3. The algorithm first optimizes the Res-Block and then improves the darknet structure by increasing the convolution operation. Y. Li et al. proposed a multiblock SSD (MBSSD) mechanism for railway scenes monitored by UAVs. MBSSD uses transfer learning to solve the problem of insufficient training samples and improve accuracy. Y. Liu et al. proposed multi-branch parallel feature pyramid networks (MPFPN) and used a supervised spatial attention module (SSAM) to focus the model on object information. MPFPN conducted experiments on a UAV public dataset named VisDrone-DET to prove its effectiveness. These algorithms are combined with UAV application scenarios but are all based on classic methods. They cannot work well when inferencing against untrained small objects

3. CONTRIBUTIONS

- **Kamarthi Litheesh Kumar** (S20190020218) - Written Arduino code, Python code for Object tracking and detection, and Website code for printing values.
- **TU Surya Sathvik** (S20190020254) - Written Python code for Drone path tracking, Hardware connections of Raspberry pi.

Problem Statement:

The object recognition and tracking of a specific object using a Tello require a method to communicate changes in the object's position as well as manipulation of the RBG values in a CV2 code. For object recognition, Tello will need to recognize the specific color of the object. The RBG values chosen for the object are unlikely to be exact, but it will need a specific range to be close enough in order for Tello to recognize the specific object. To track the object, the Tello will need to process that there is an offset in the original distance of the object from the center of the frame and react accordingly to refocus.

4. METHODOLOGY

In this project, We want to collect data without any loss for that we have node points where the total data from the sensors like Temperature sensor, Humidity sensor, Rainfall sensor, and Soil Moisture sensors will be calculated. From these sensors, data will be collected by ground Raspberry pi and then send to the cloud using the MQTT protocol. When a drone having raspberry pi reaches the range of ground raspberry pi, the data will be transmitted and the drone raspberry pi will send that data to the cloud. In the cloud, we are training the data and after identifying that the reading is out of thresholds then we can activate the process manually when the soil moisture is very low then we can turn ON the pump motor which can wet the soil and help us to get a good yield.

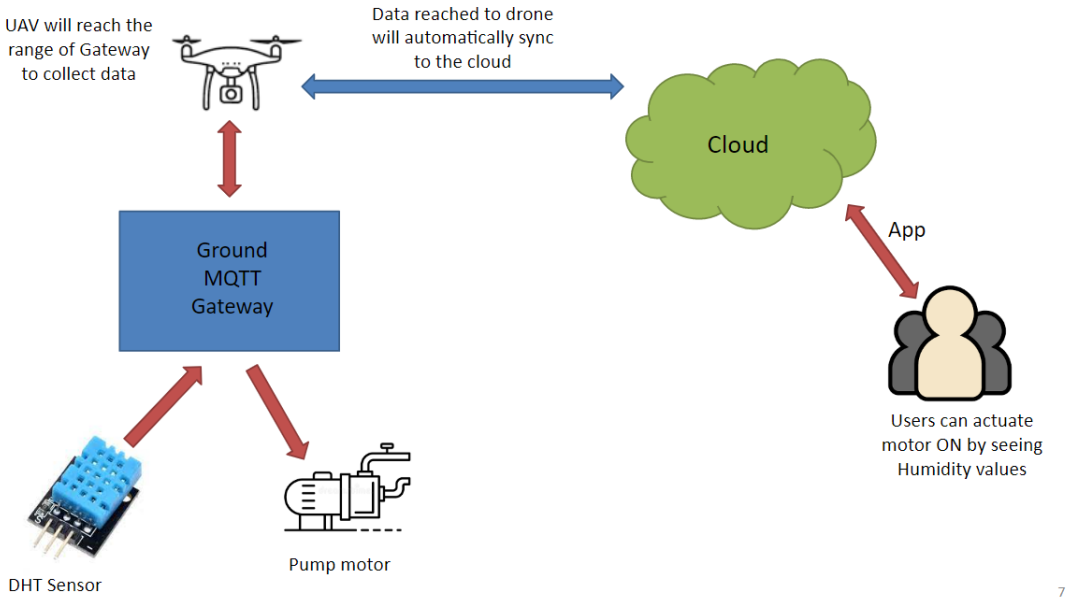


Figure1: Flow chart of ground Raspberry pi connections

4.1. Definition:

For the transmission of data we are using the MQTT protocol. MQTT(MQ Telemetry Transport) is a lightweight, publish-subscribe, machine-to-machine network protocol for Message queue/Message queuing service. It is designed for connections with remote locations that have devices with resource constraints or limited network bandwidth. It must run over a transport protocol that provides ordered, lossless, bi-directional connections—typically, TCP/IP.

4.2. Overview:

The MQTT protocol defines two types of network entities: a message broker and a number of clients. An MQTT broker is a server that receives all messages from the clients and then routes the messages to the appropriate destination clients. An MQTT client is any device (from a microcontroller up to a fully-fledged server) that runs an MQTT library and connects to an MQTT broker over a network.

Information is organized in a hierarchy of topics. When a publisher has a new item of data to distribute, it sends a control message with the data to the connected broker. The broker then distributes the information to any clients that have subscribed to that topic. The publisher does not need to have any data on the number or locations of subscribers, and subscribers, in turn, do not have to be configured with any data about the publishers.

If a broker receives a message on a topic for which there are no current subscribers, the broker discards the message unless the publisher of the message designated the message as a retained message. A retained message is a normal MQTT message with the retained flag set to true. The broker stores the last retained message and the corresponding QoS for the selected topic. Each client that subscribes to a topic pattern that matches the topic of the retained message receives the retained message immediately after they subscribe. The broker stores only one retained message per topic. This allows new subscribers to a topic to receive the most current value rather than waiting for the next update from a publisher.

When a publishing client first connects to the broker, it can set up a default message to be sent to subscribers if the broker detects that the publishing client has unexpectedly disconnected from the broker. Clients only interact with a broker, but

a system may contain several broker servers that exchange data based on their current subscribers' topics.

A minimal MQTT control message can be as little as two bytes of data. A control message can carry nearly 256 megabytes of data if needed. There are fourteen defined message types used to connect and disconnect a client from a broker, to publish data, to acknowledge receipt of data, and to supervise the connection between client and server. MQTT relies on the TCP protocol for data transmission. A variant, MQTT-SN, is used over other transports such as UDP or Bluetooth.

4.3. MQTT broker:

The MQTT broker is a piece of software running on a computer (running on-premises or in the cloud), and could be self-built or hosted by a third party. It is available in both open-source and proprietary implementations. The broker acts as a post office. MQTT clients don't use a direct connection address of the intended recipient but use the subject line called "Topic". Anyone who subscribes receives a copy of all messages for that topic. Clients can subscribe to a topic from a single broker, and single client can register subscriptions to topics with multiple brokers.

Each client can both produce and receive data by both publishing and subscribing, i.e. the devices can publish sensor data and still be able to receive the configuration information or control commands (MQTT is a bi-directional communication protocol). This helps in sharing data and managing and controlling devices. A client can not broadcast the same data to a range of topics and must publish multiple messages to the broker, each with a single topic given.

With the MQTT broker architecture, the client devices and server applications become decoupled. In this way, the clients are kept unaware of each other's information. MQTT, if configured, can use TLS encryption with the certificate, username, and password-protected connections. Optionally, the connection may require certification, in the form of a certificate file that a client provides and must match with the server's copy.

In case of failure, the broker software and clients can automatically hand over to a redundant/automatic backup broker. Backup brokers can also be set up to share a load of clients across multiple servers on-site, in the cloud, or a combination of these. The broker can support both standard MQTT and MQTT for compliant specifications such as Sparkplug. This can be done with the same server, at the same time, and with the same levels of security.

The broker keeps track of all the session's information as the device goes on and off, in a function called "persistent sessions". In this state, a broker will store connection info for each client, topics each client has subscribed to, and any messages for a topic with a QoS of 1 or 2.

The main advantages of an MQTT broker are:

- Eliminates vulnerable and insecure client connections if configured to
- Can easily scale from a single device to thousand devices
- Manages and tracks all client connection states, including security credentials and certificates, if configured to
- Reduced network strain without compromising the security if configured to (cellular or satellite network)

Here we are using two NodeMCUs as end clients. The NodeMCU which is connected to the LED bulb acts as a Subscriber and another one which is connected to the DHT sensor acts as Publisher and Raspberrypi links both ends using the MQTT protocol to act as MQTT broker. The publisher wants to publish data sensed from the DHT sensor and LED will subscribe to the data from raspberry pi which tells the subscriber to turn it ON then LED will glow. These MQTT connections help us to transmit the data from one endpoint to another point.

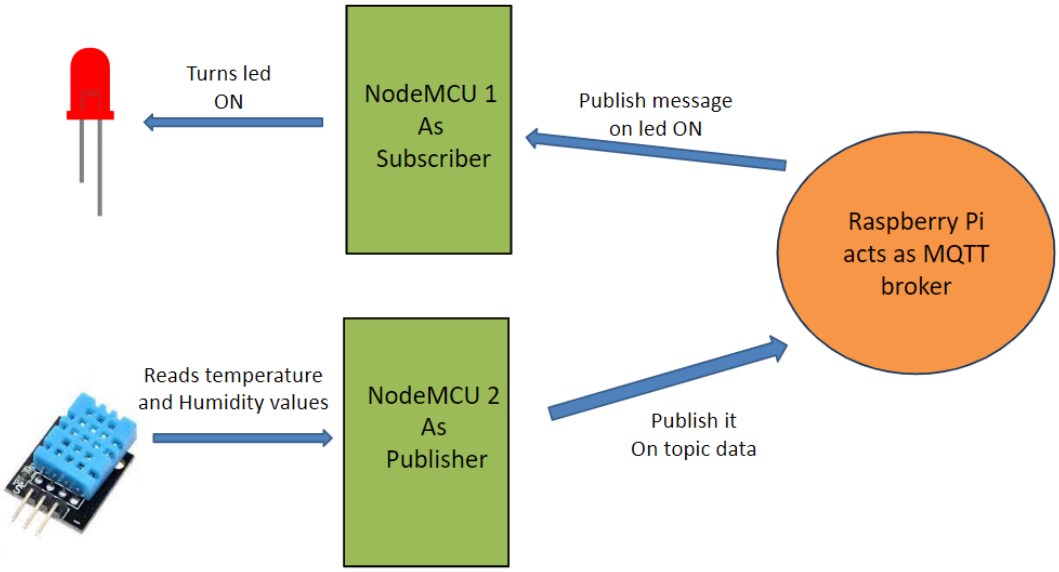


Figure2: Basic MQTT connection between 2 NodeMCUs

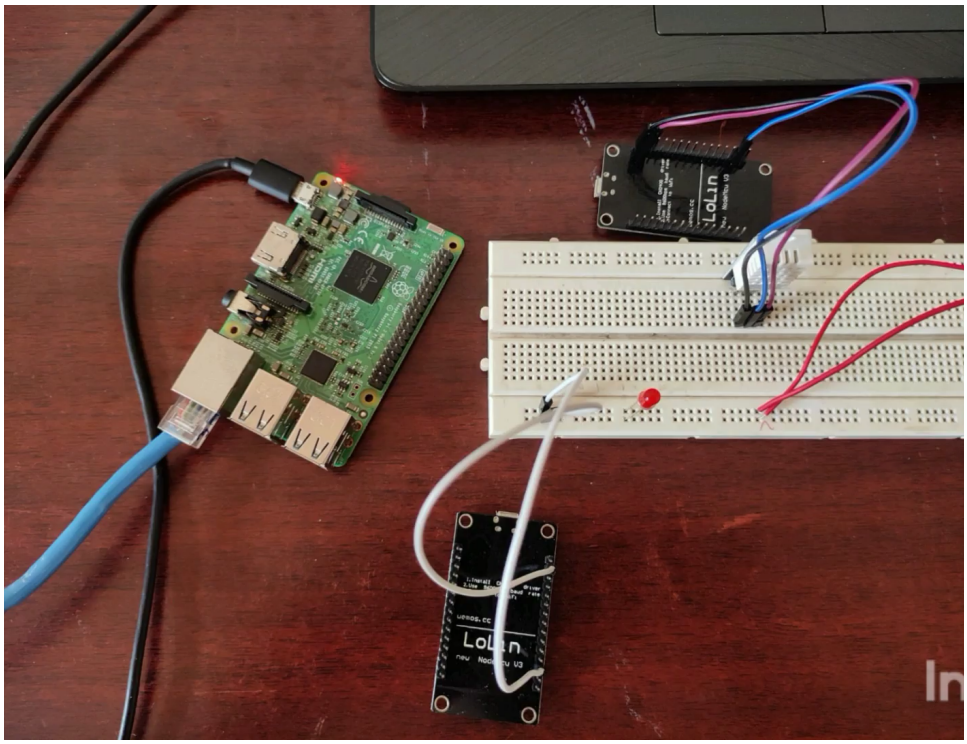
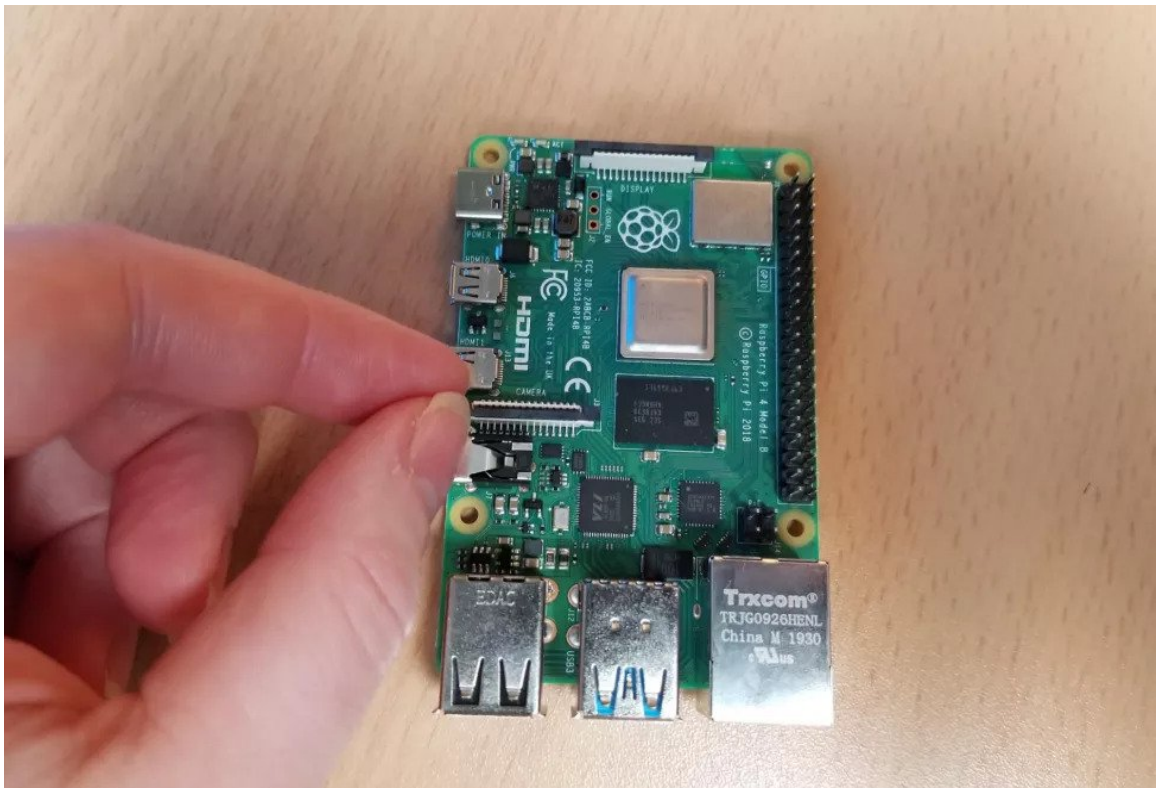


Figure3: Hardware of figure 2 MQTT connections

4.4. After that we extended the scale to litter higher, Now we are streaming the video taken from the raspberry pi camera module and can show photos taken by it. For that we have followed the below steps:

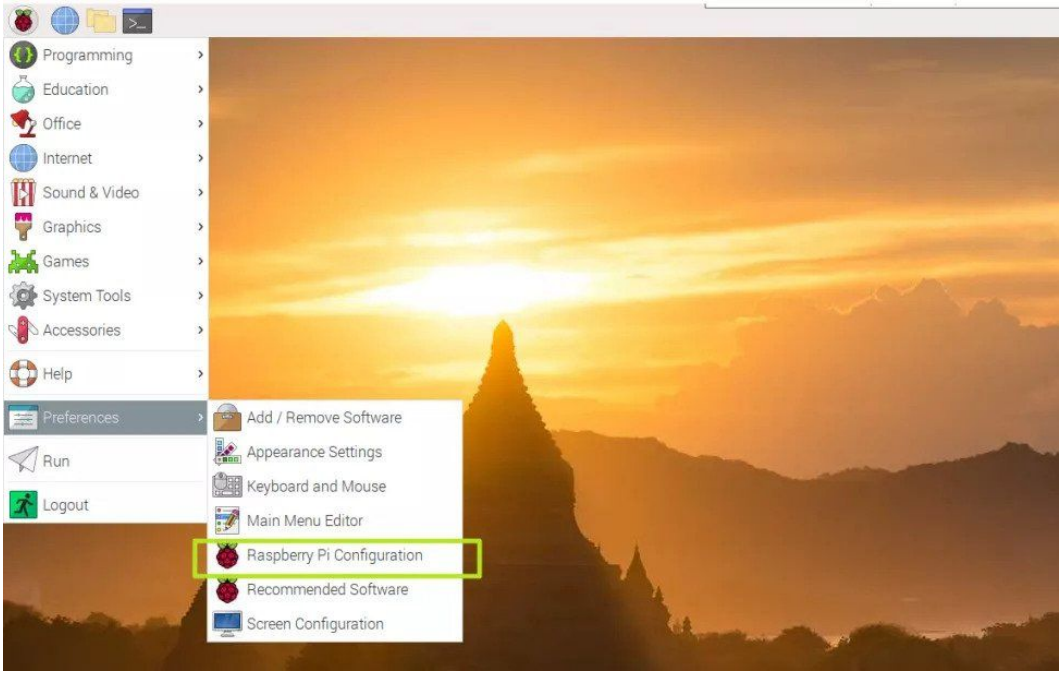
1. Open the camera port by gently lifting the plastic lock upwards.



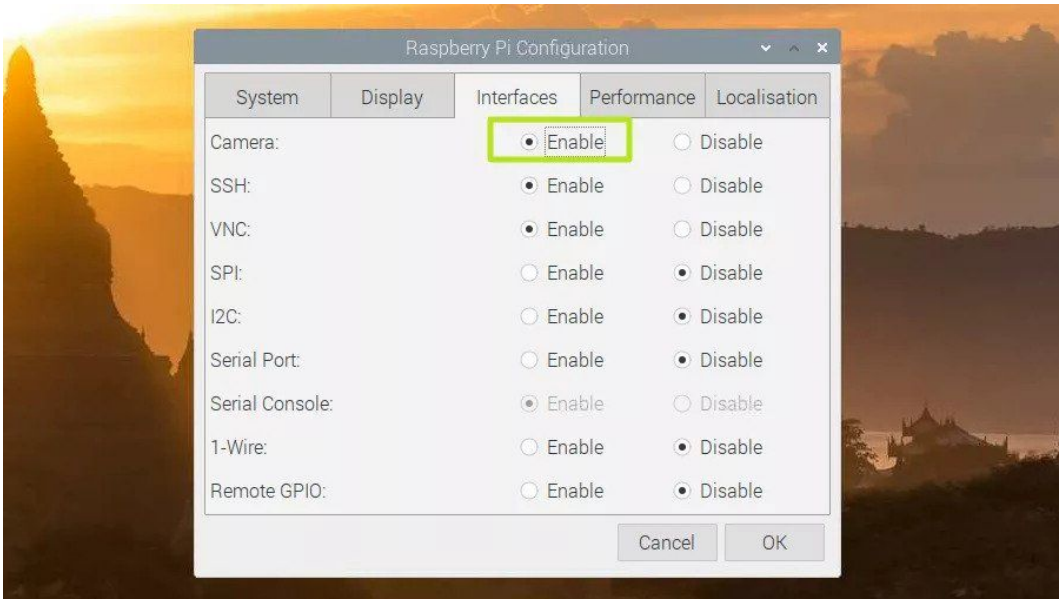
2. Insert the ribbon connector with the blue tab facing the USB / Ethernet ports.

3. Close the lock on the connector and give it a very gentle pull to make sure it is in place.

4. Power up your Raspberry Pi and then go to Preferences >> Raspberry Pi Configuration.



5. Click on the Enable button for the Camera found in the Interfaces tab.



6. Click Ok and reboot the Pi.

7. Open a Terminal and type the following command to take a quick picture to test the camera.

```
$ raspistill -o test.jpg
```

After five seconds have elapsed, an image will be taken and saved as test.jpg. Using the file manager check that the image is correct before moving on.

4.5. Testing a Stream

To start a stream we need to open a terminal and enter a rather long command. Ensure that your Raspberry Pi is connected to the network. For the best performance use an Ethernet cable, Wi-Fi will work, but you may see dropouts.

1. **Get the hostname of your Raspberry Pi**. Open a terminal and type in this command for your hostname. Make a note of the hostname. You may need to add ".local" to the end, depending on your network.

```
$ hostname
```

2. **Run the streaming command**. The one-line command to run a video stream live from the camera is rather long, so let's go through the command before we run it.

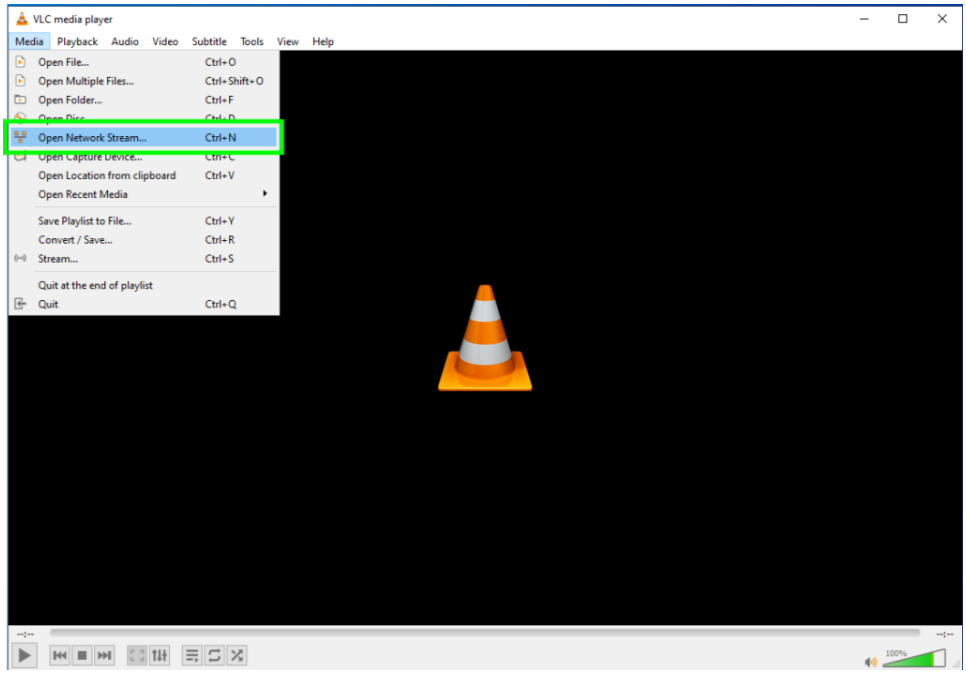
   -o is our output, in this case, set to none.
   -t is the length of the video clip, using zero will set this to infinite.
   -w and -h are the width and height of the video, in this case, 800 x 600.
   -fps is the frames per second for the video stream, a lower value should minimize dropouts.

   Run this command in a terminal on your Raspberry Pi.

```
raspivid -o - -t 0 -w 800 -h 600 -fps 12  | cvlc -vvv
stream:///dev/stdin --sout '#rtp{sdp=rtsp://:8080/}'
                    :demux=h264
```

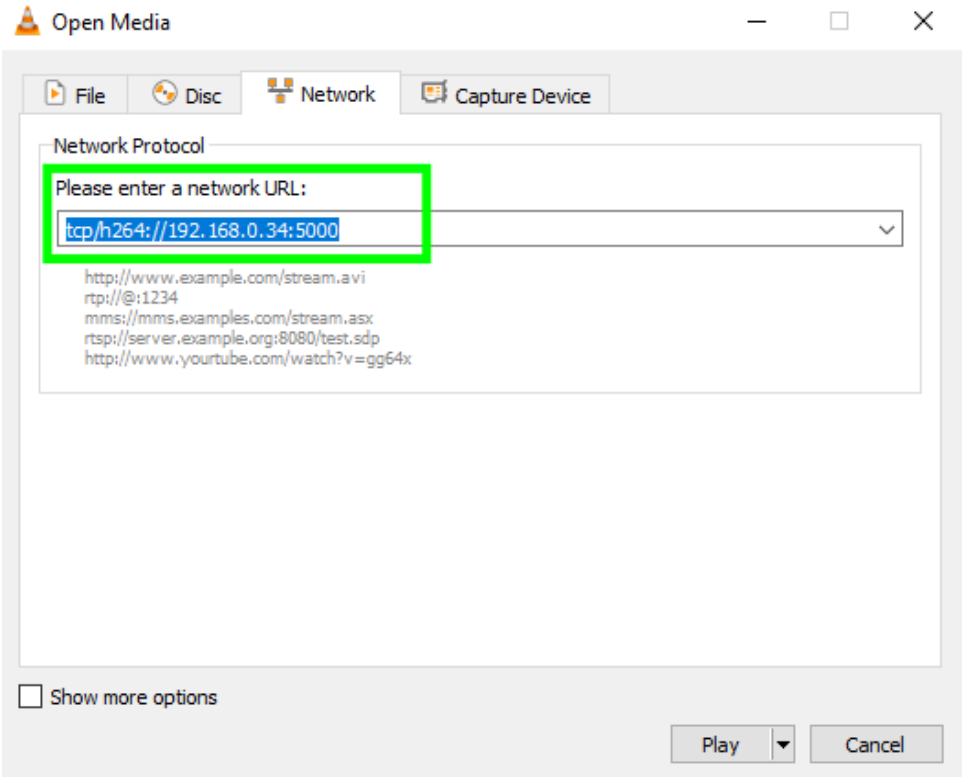
3. On your Windows / Mac / Linux computer install VLC and then open VLC.

4. Go to Media >> Open Network Stream, or press CTRL + N.



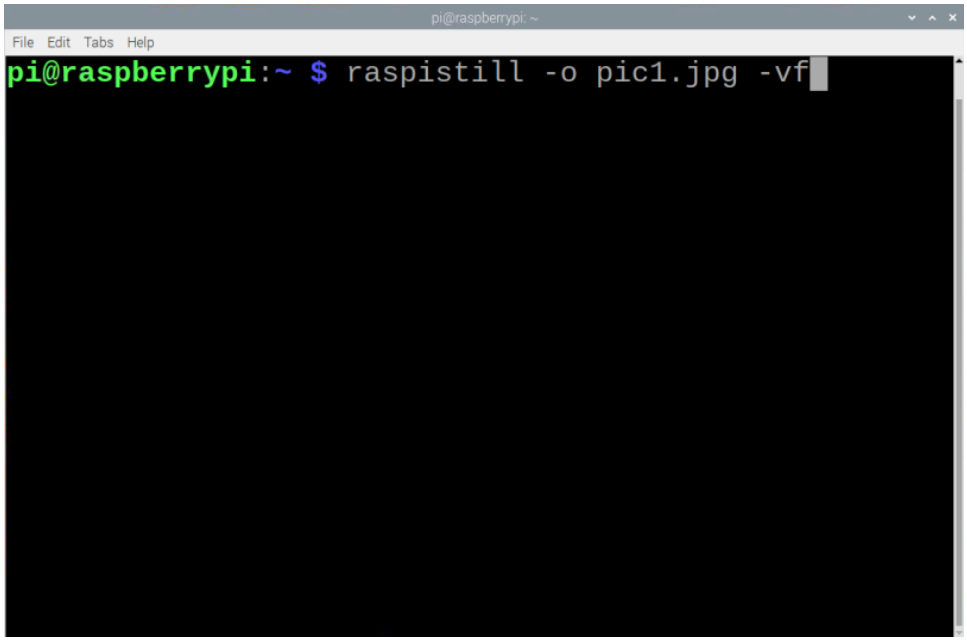
5. Enter the rtsp address and port of your Raspberry Pi. The rtsp address is your Raspberry Pi's hostname, prefixed with rtsp://, and the port was set to 8080. Click Play to start the stream. Here is our example rtsp address.

```
rtsp://raspberrypi:8080/
```

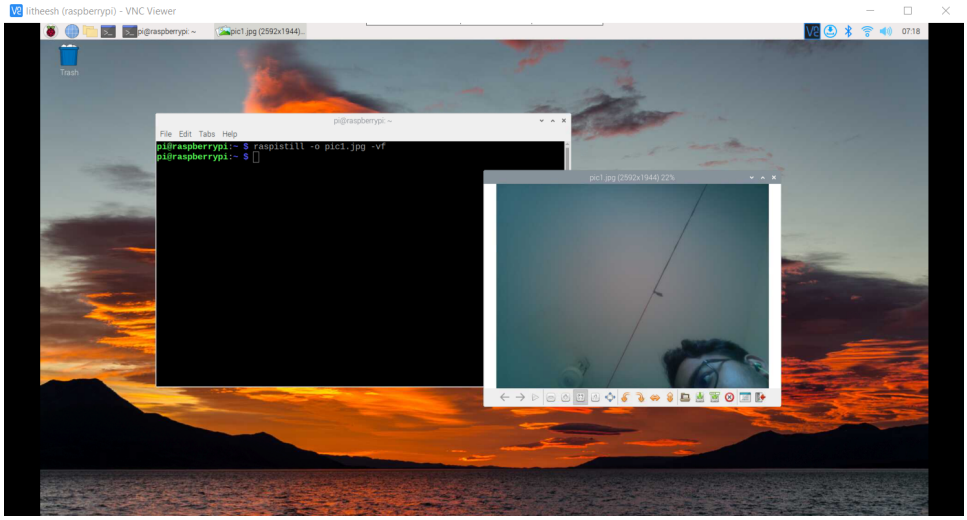


It will take VLC a few seconds to catch up with the stream, be patient. Soon you will see video streamed from your Raspberry Pi, with a delay of around 5 to 10 seconds.

6. To record a stream, click on Playback >> Record and then specify a filename. The recording will end when the stop button is pressed.



Command for Raspberry pi camera module taking photos



Raspberry pi taking photos

4.6. Streaming Video With RPi

1. Use raspivid to create an infinite stream at a resolution of 800 x 600 at 15 fps. The -ifx switch will be populated by a randomly chosen effect from the array To stream live video, this time we use a standard TCP stream. It works a little faster than rstp but your stream may have artifacts. The Pi listens (-l) for connections from any local IP address.

```
raspivid -t 0 -w 800 -h 600 -ifx ${array[$index]} -fps 15 -l
                    -o tcp://0.0.0.0:5000
```

2. Save the code to the /home/pi/ directory and exit from the editor.
3. Open a terminal and use this command to make the code executable.

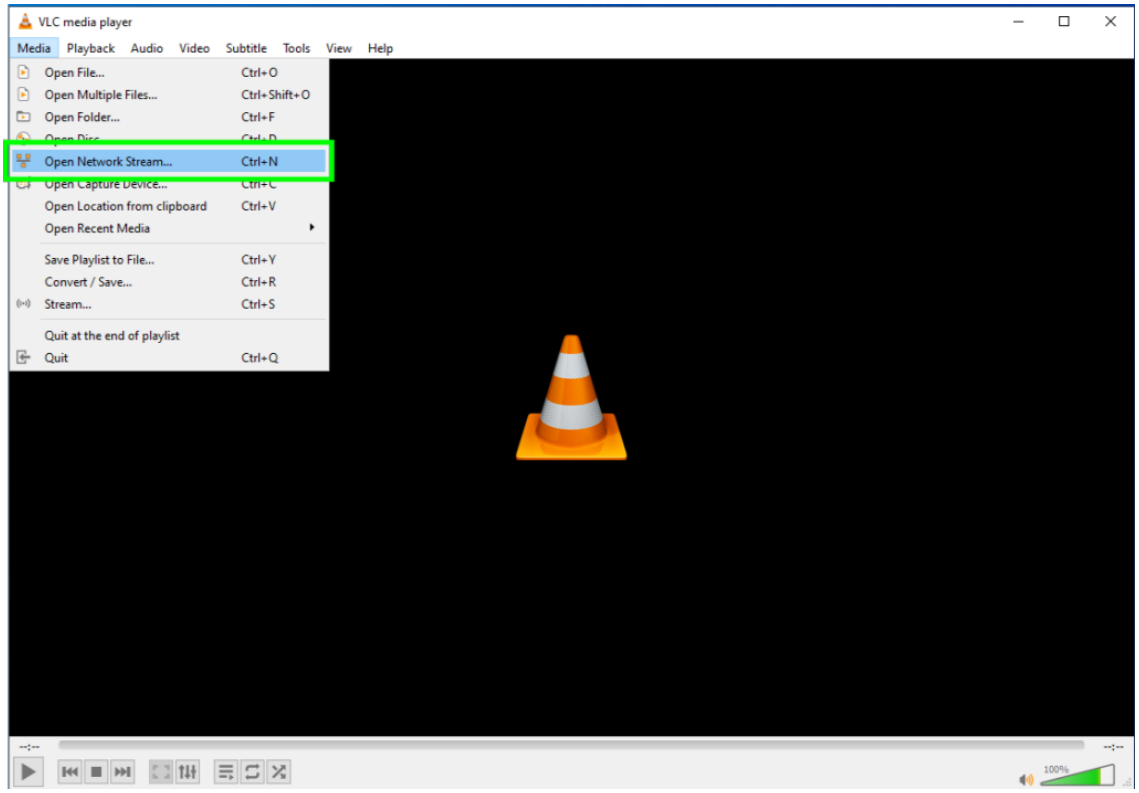
```
$ chmod +x random_stream.sh
```

4. Run the code.

```
$ ./random_stream.sh
```

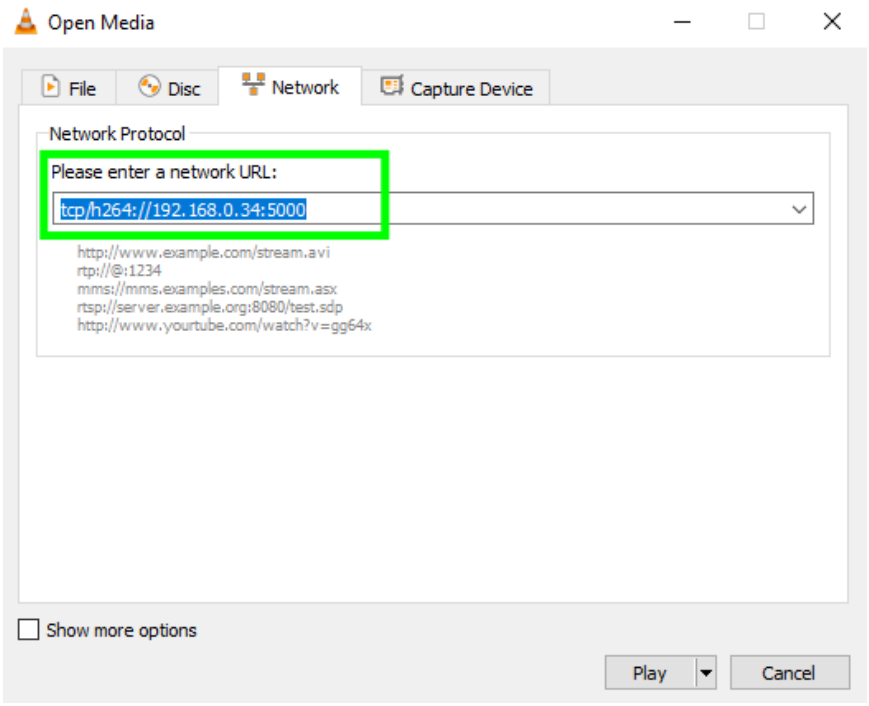
5. On your Windows / Mac / Linux computer open VLC.

6. Go to Media >> Open Network Stream, or press CTRL + N.



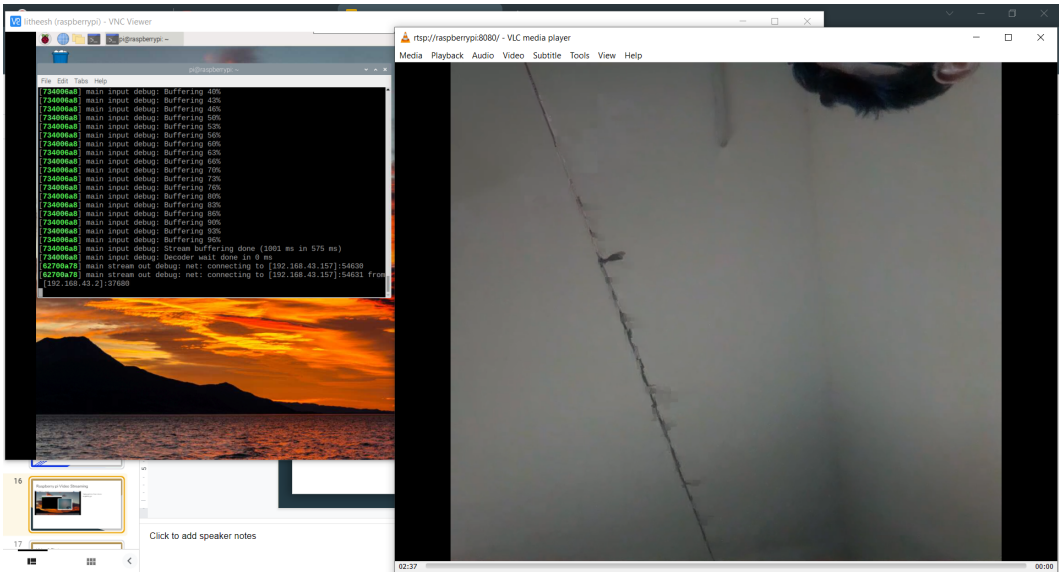
13. Enter the TCP address and port of your Raspberry Pi. The TCP address is the Raspberry Pi's hostname, prefixed with tcp/h264://, and the port is set to 5000. Click Play to start the stream. Here is our example TCP address.

```
tcp/h264://raspberrypi.local:5000
```



14. To record a stream, click on Playback >> Record and then specify a filename. The recording will end when the stop button is pressed.

Command for raspberry pi for video streaming



Live streaming from raspberry pi in VLC Player

Here is the full flow chart of our project which consists of all submodules from starting where IoT connection is given using MQTT protocol and the data will be sent to drone raspberry pi. Video streaming by drone raspberry pi camera module. Data from the cloud will be visible on the Website. When the algorithm identifies outliers then we can actuate the processes like turning ON pump motor.

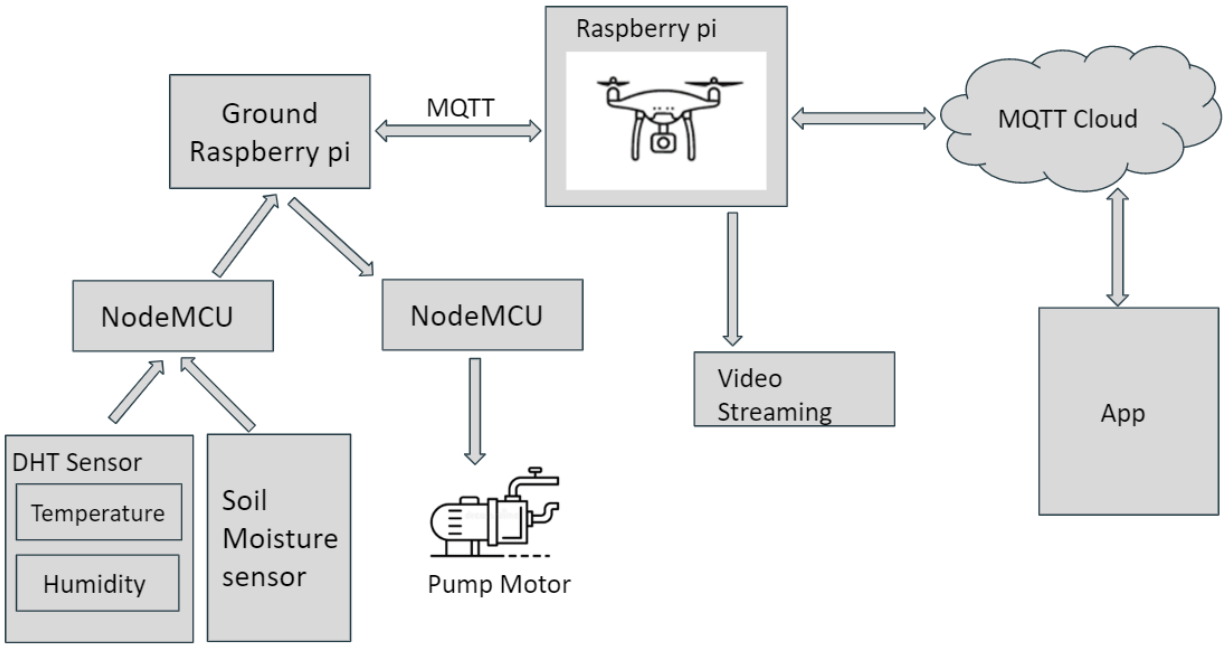


Figure4: Full flow chart of the project

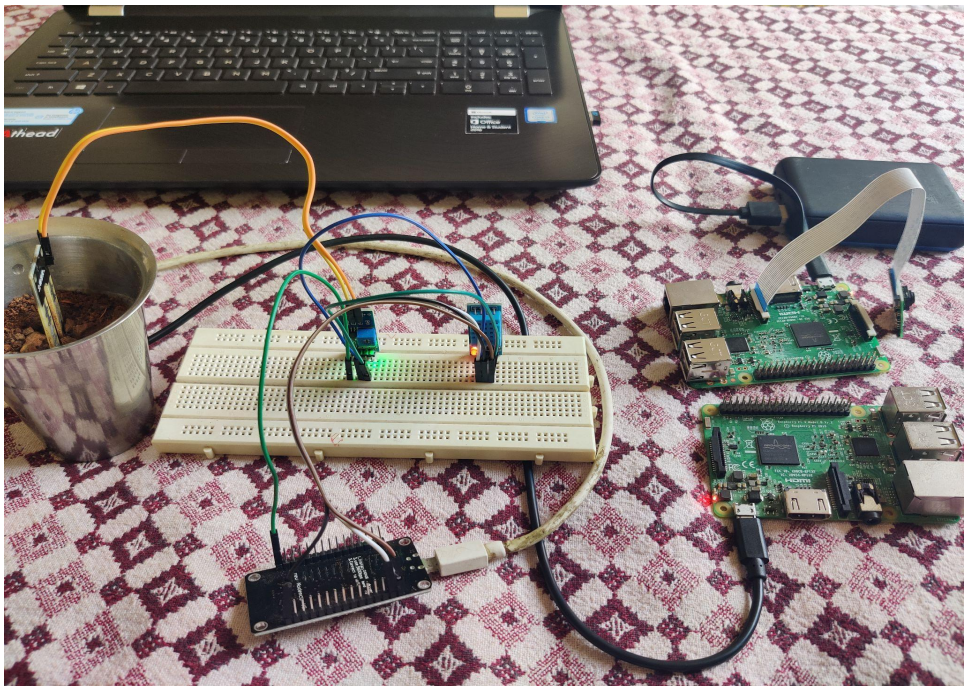


Figure5: Hardware connections of the project

Links for Arduino coding [Click here]

4.7. Tello Drone Object Tracking:

You may actually use any programming language that can establish a UDP connection to send commands to the Tello drone, however, for this project, we will use Python to send commands to the drone. Python programming is intermediate to advanced subject.

Once the DJI Tello can be controlled remotely, the next step to color tracking is to display the camera feed that the Tello sees on the computer using CV2. The pixels in the image can be searched for pixels of a certain color by analyzing RGB values. In this project, we used a range of violet values. The code will blur together pixels within the largest area blue color range and draw a circle around the violet object we hope to track.

Tracking the object is done using a PID control loop incorporating the offset coordinates of the center of the object and the center of the frame. This is done by using the coordinates from the previous frame and comparing it to the current frame. These coordinate distances are computed in pixels. The goal of tracking is to track where the blue object is "now" based off where it was in the last frame.

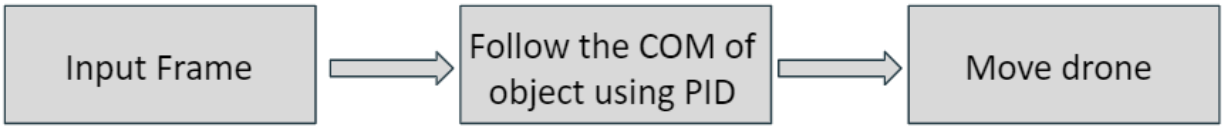
The control loop uses the offset coordinates and the distance from the center to find velocities. These velocities are used to command the drone to move left, right, up, or down. It runs the loop for each frame and moves the drone accordingly. The drone should move either up, down, left, or right by observing the sign of the velocity in either the x or y direction. The velocity at which the drone moves is the magnitude of the value computed by the control loop. All of this should result in a drone tracking a violet object.

From tello we can take photos and record video manually and automactically by python coding. Here are the links forpython coding we used for operating the Tello drone in this project

Link for Python code [Click here]

4.8.Basic Steps for Object tracking:

- Identify different objects in the captured image based on the color.
- Convert image to an HSI plane (HUE, SATURATION, and INTENSITY)
- We get the binary mask of our object.
- Try to put the COM of the object in the frame.
- Use PID to calculate the speed and movements of the drone.



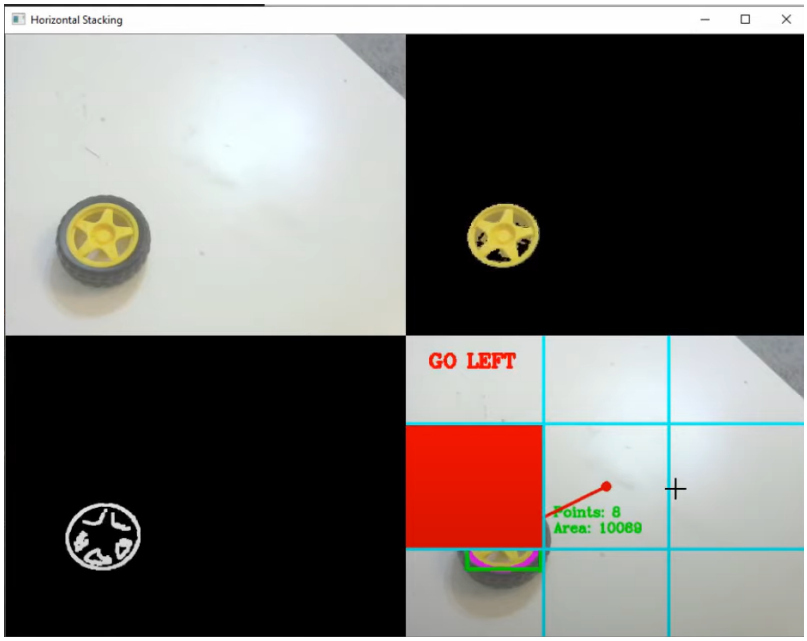


Figure6:Example of Stacking of all results

Quadrant1: Image was taken by drone

Quadrant2: Blurring all colors other than required color

Quadrant3: converting an RGB image to HSI image

Quadrant4: Now we draw a boundary region around all required points. If the center of the object deviates from the center of the frame then it popups to correct its frame by saying GO LEFT, GO RIGHT, GO TOP, GO BOTTOM, etc...

Link to Python Code to Object Detection and Tracking [Click here]

Gdrive link of photos taken by Tello drone [Click here]

Video link of the Phase 2 Work [Click here]

4.9. Dronepath tracking:

We assigned Tello a dedicated path and Tello uses computer vision algorithms in python to detect objects using colors and moves along this path when it reaches the node point of the IoT connection. Given the drone, the path is in figure 10. So at first drone starts from its starting position(Helipad) and reaches the first tree (numbered 1) and collects data from its node and sends the data to the cloud and the same way it collects data from all the trees and reaches its starting position.

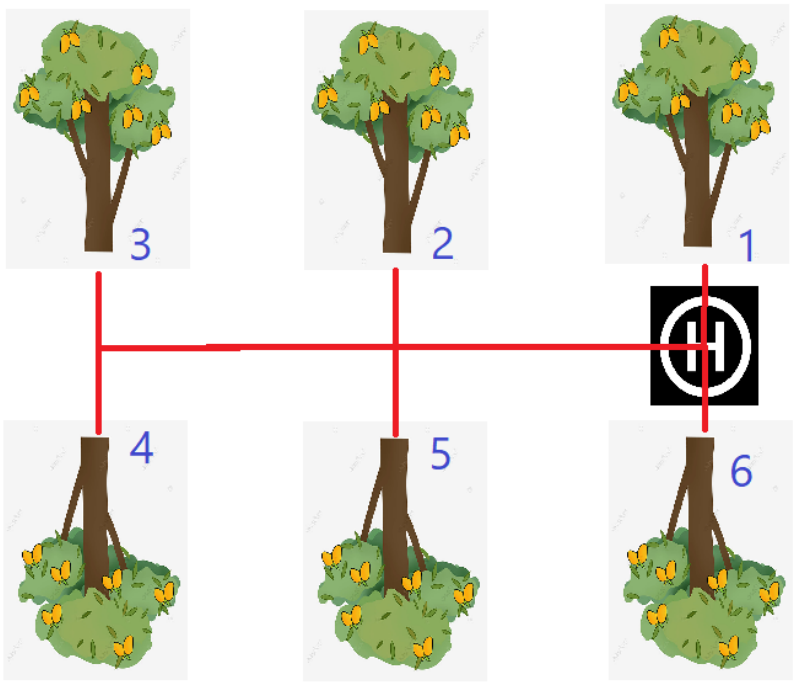


Figure7. Assigned Tello drone path

Link for python code of drone path [Click here]

Google drive link for pics and video taken by Tello [Click here]

Link for Website Source code [Click here]

Explanation of Code:

The code below will use Python to fly your Tello drone on a pre-determined flight path. There are four main Python files.

- stats.py defines the Stats object to store statistics on command requests and responses
- tello.py defines the Tello object to abstract and represent the Tello drone
- command.txt stores the commands that will be sent to the Tello drone
- app.py is the application program, or the driver, that will be executed as an entry point to start sending commands

Here, we can have the sample code of drone while the drone is flying to the tree (numbered 1). Firstly, we want to know the measurements of the experiment that is the distance between both the trees (numbered 1 and 2) is 500 centimeters, and the trees (numbered 1 and 6) are 400 centimeters.

```
# tree 1-----------------------------------
    me.tello.move_forward(200)     # Forward 200cms
    def TelloObjectTracking(self):# Run program
    return self.tello()
    me.tello.rotate_cw(180)        # Rotate 180 degrees clockwise
    me.tello.move_forward(200)     # Forward 200cms
    me.tello.rotate_cw(90)         # Rotate 90 degrees clockwise
    me.tello.move_forward(500)     # Forward 500cms
    me.tello.rotate_cw(90)         # Rotate 90 degrees clockwise
```

The drone starts flying from the starting position (Helipad symbol) travels to each tree as numbered and for that drone will move forward 200 centimeters ie. (from helipad to tree1) then it will collect data from sensors and send to the cloud which will be done by running TelloMain.py and the stabilization and object tracking for to get into its trajectory will be done by TelloObjectTracking.py. After that drone will rotate 180 degrees clockwise, then moves forward to reach the horizontal drone path line ie. 200 centimeters far from its last position.

Now drone will rotate 90 degrees to face the path, then moves forward 500 centimeters to reach another tree path. After that, it will rotate 90 degrees to face the tree. In the same way, the drone will collect all the data from the trees and reach its starting destination. All the codes are in the above-given links.

4.10. Data visible on the Website:

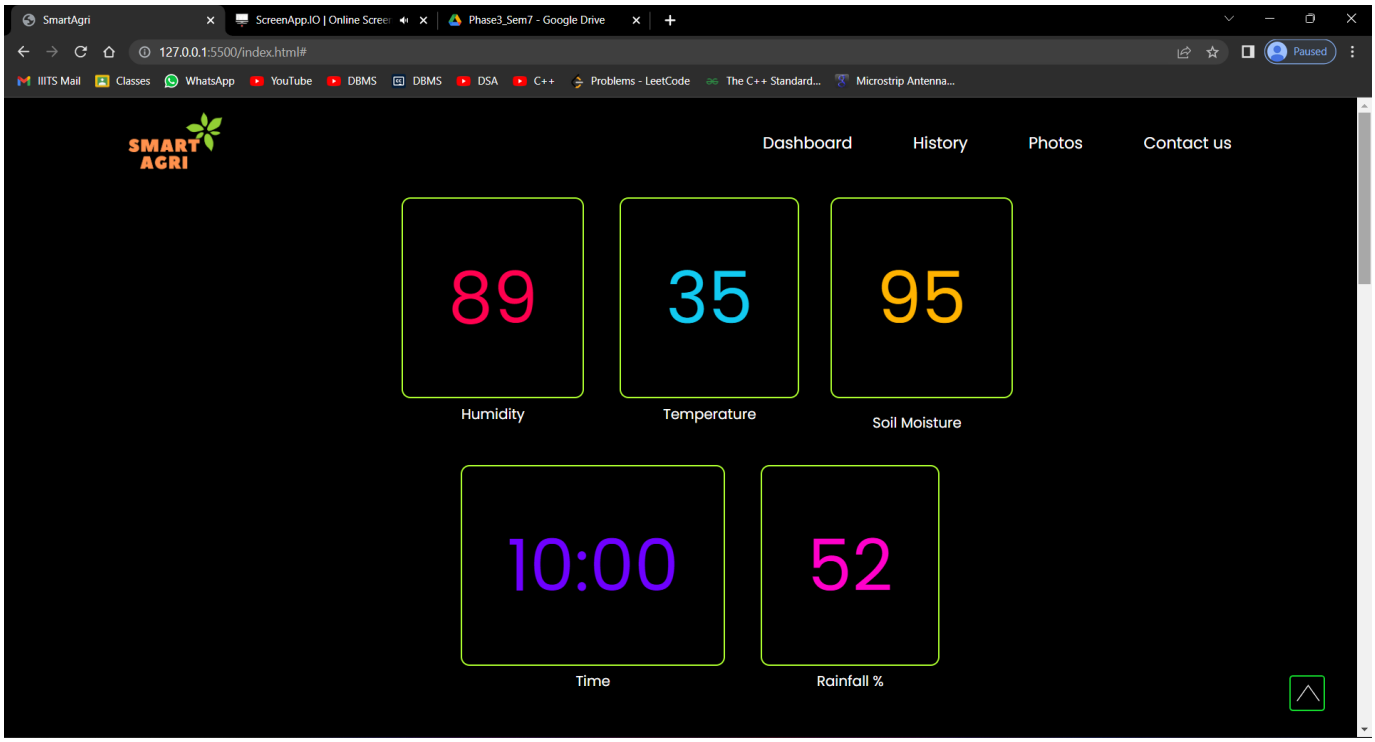
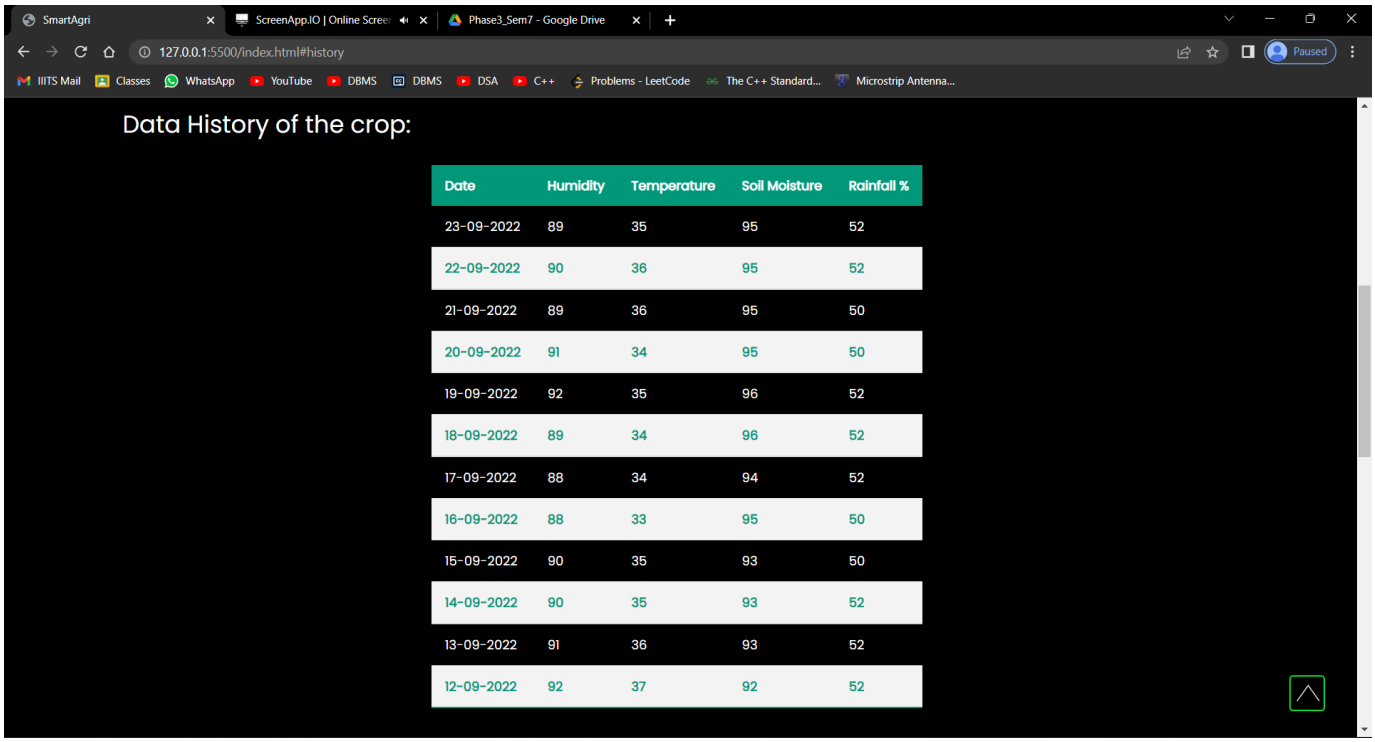


Figure8. Screenshot of Website dashboard



Date	Humidity	Temperature	Soil Moisture	Rainfall %
23-09-2022	89	35	95	52
22-09-2022	90	36	95	52
21-09-2022	89	36	95	50
20-09-2022	91	34	95	50
19-09-2022	92	35	96	52
18-09-2022	89	34	96	52
17-09-2022	88	34	94	52
16-09-2022	88	33	95	50
15-09-2022	90	35	93	50
14-09-2022	90	35	93	52
13-09-2022	91	36	93	52
12-09-2022	92	37	92	52

Figure9. screenshot of website data history column

5. RESULTS

Video links of final results [Click here]

Table 1: Delay in streaming video and taking photos using raspberry pi camera module

Resolution	Delay in Streaming Video	Delay in taking Photo
1080x700	4 sec	0.5 sec
2500x1080	5 sec	1.2 sec
2592x1944	6.5 sec	3 sec

5.1. Results from MQTT connection from figure 3:

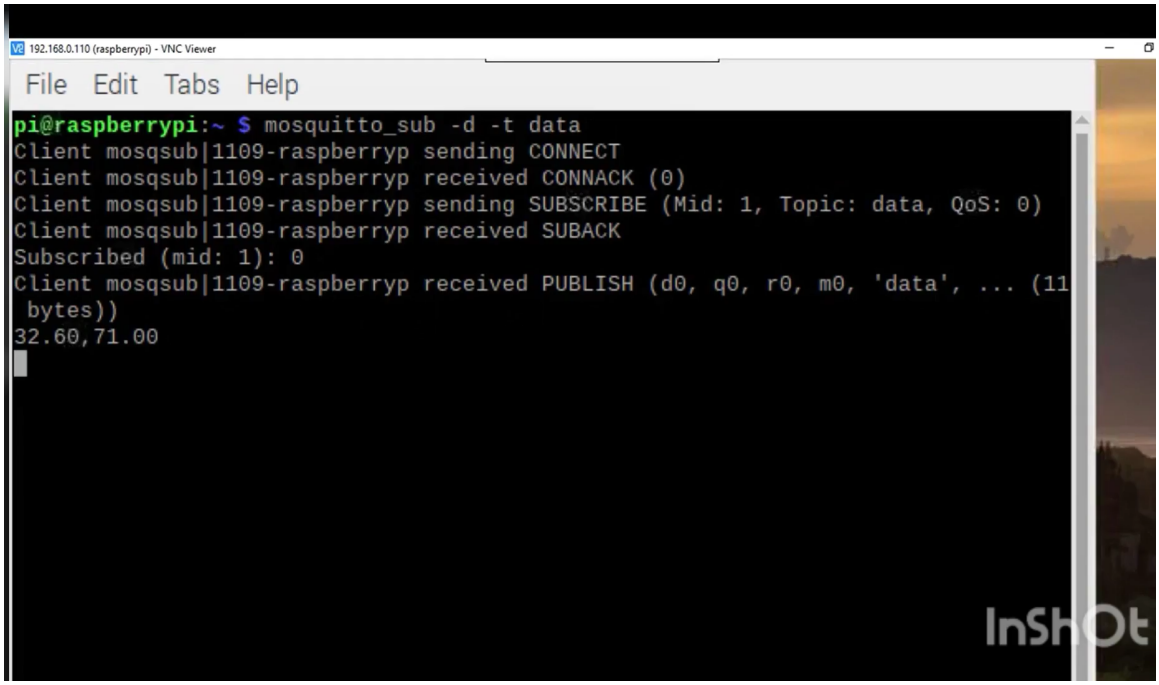


Figure10. MQTT Publisher part output

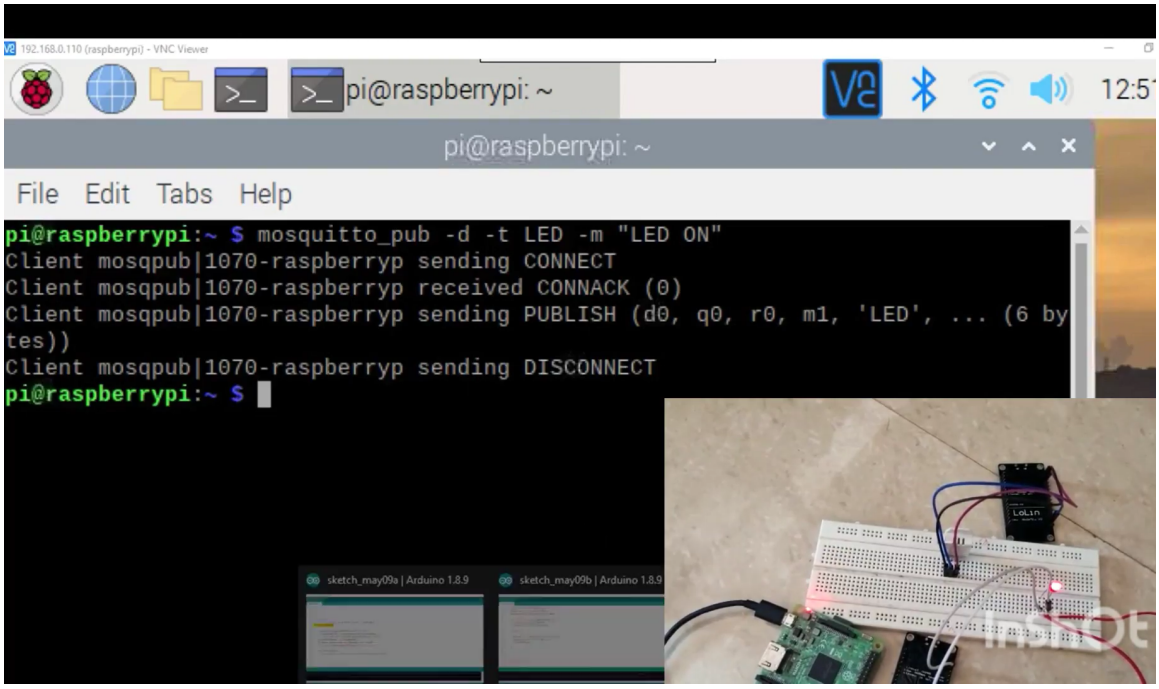


Figure11. MQTT Subscriber part output

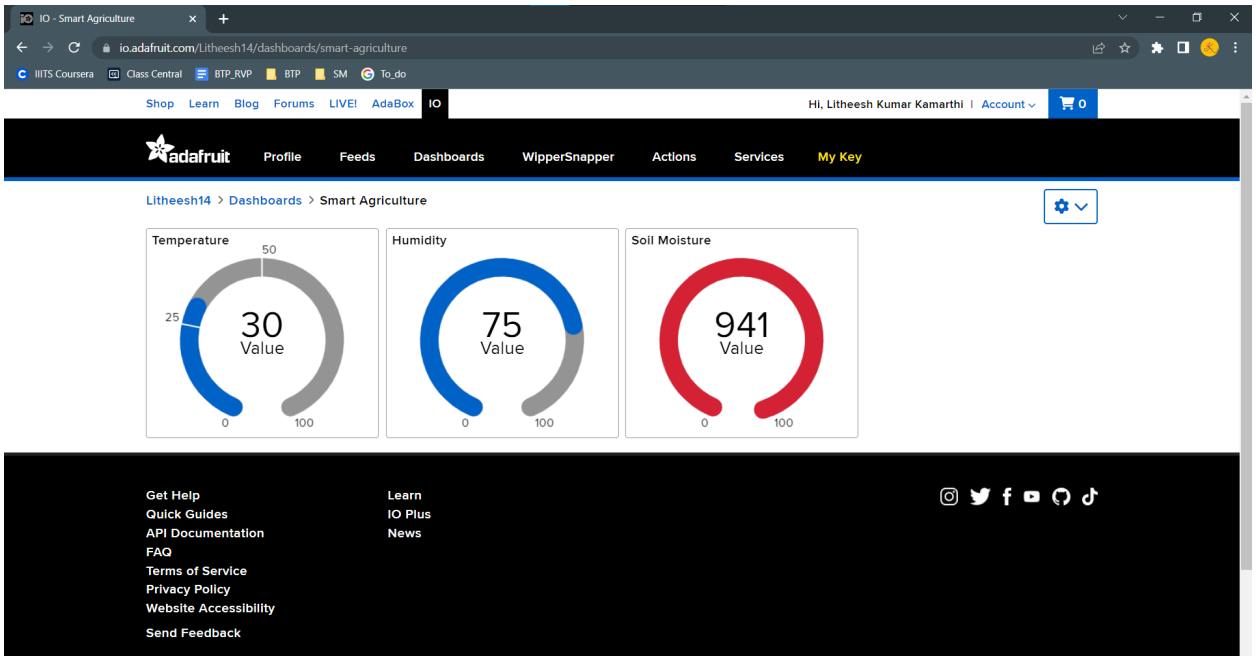


Figure12. Adafruit Cloud output

5.2. Results from Tello drone Python coding:

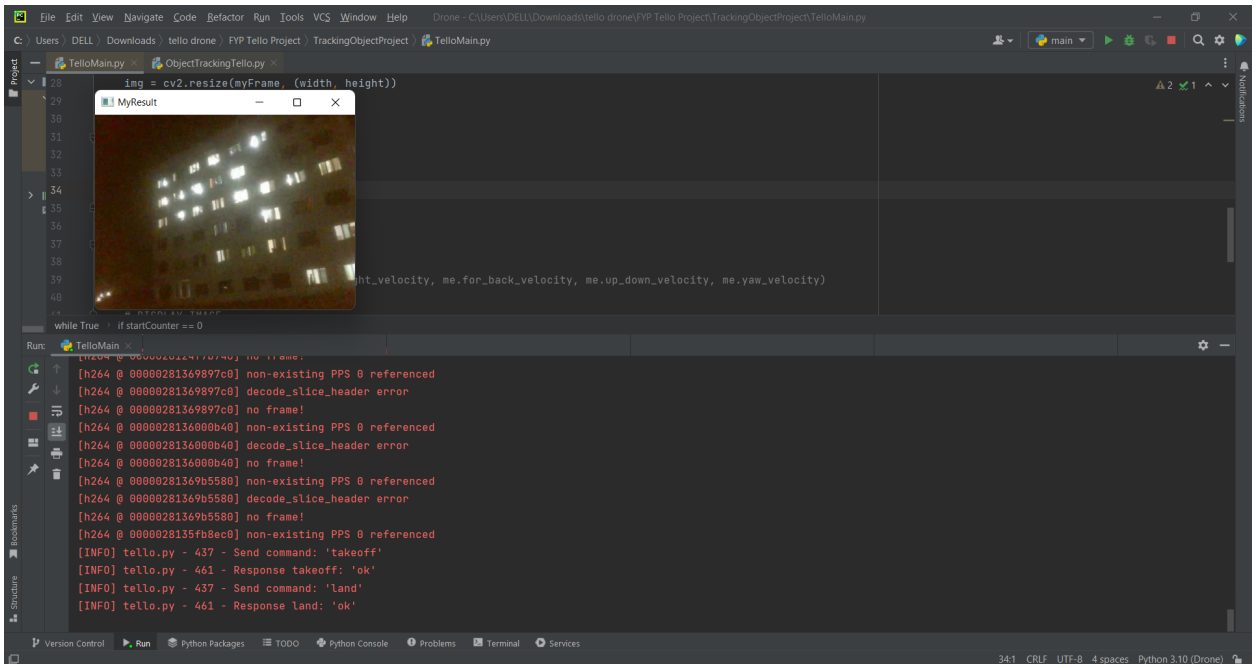


Figure13. Image taken by in automated python command mode

Figure14. Tello drone flying

Figure15. Photo of Tello drone tracking its assigned color region

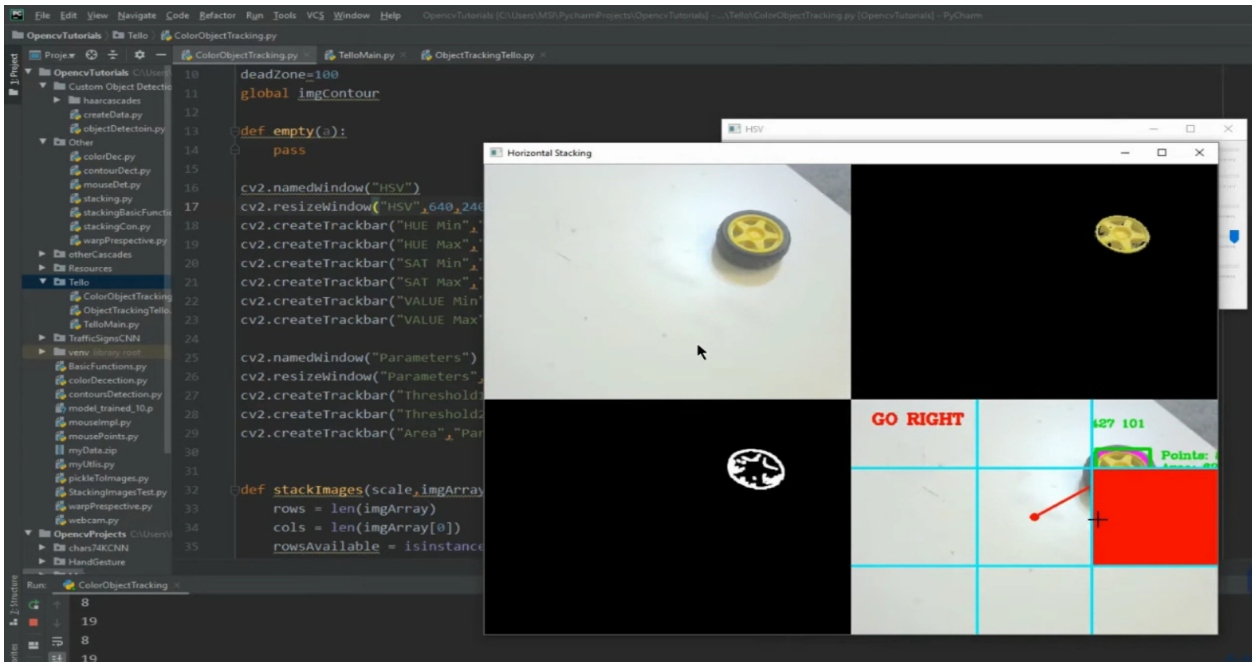


Figure16. Screenshot of stacking

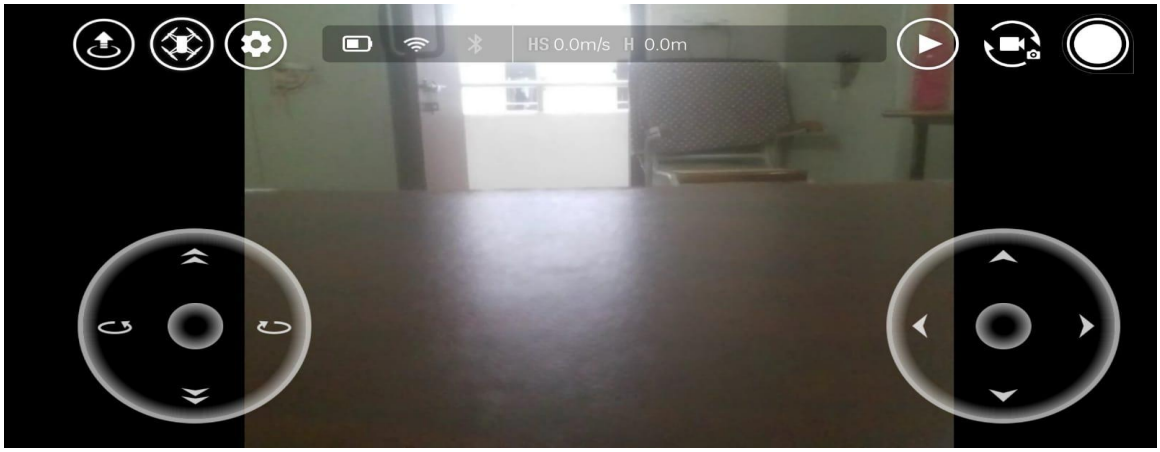


Figure17. Tello drone manual mode flying joy stick in Tello mobile app

5.3. Results from Tello drone Object tracking:

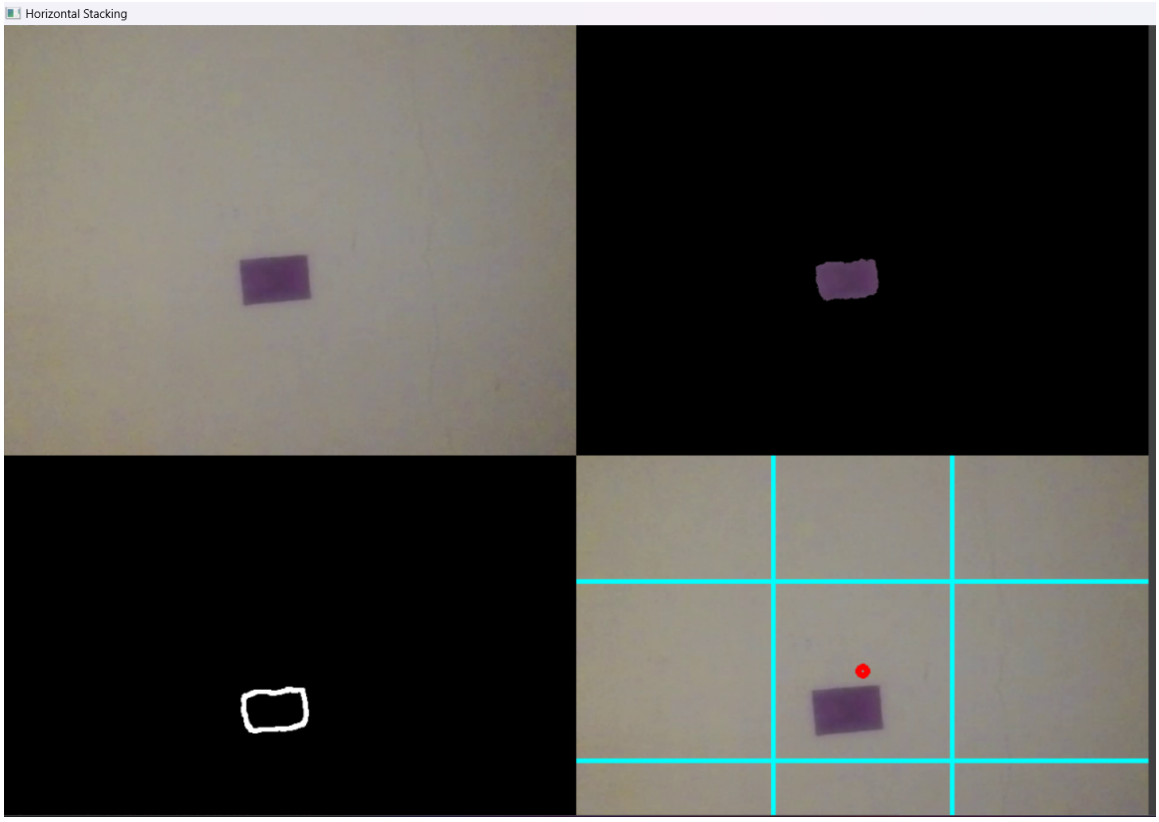


Figure18. Stacking of images

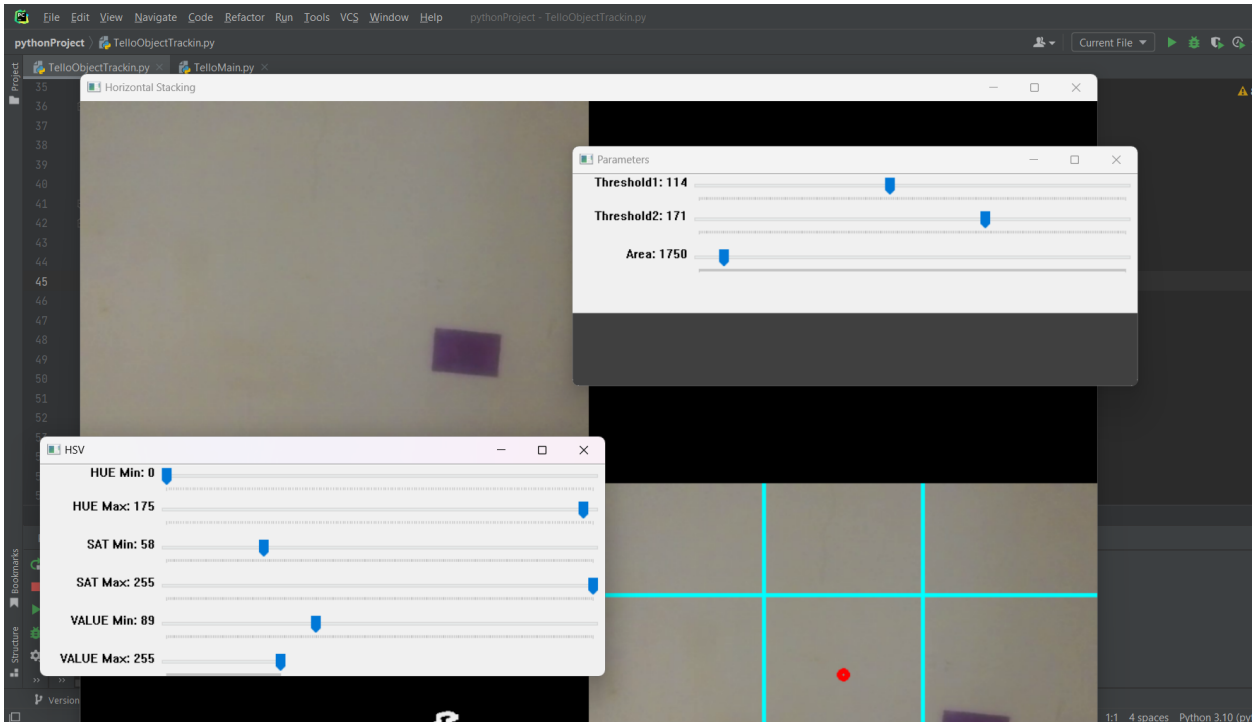


Figure19. Adjusting Threshold values

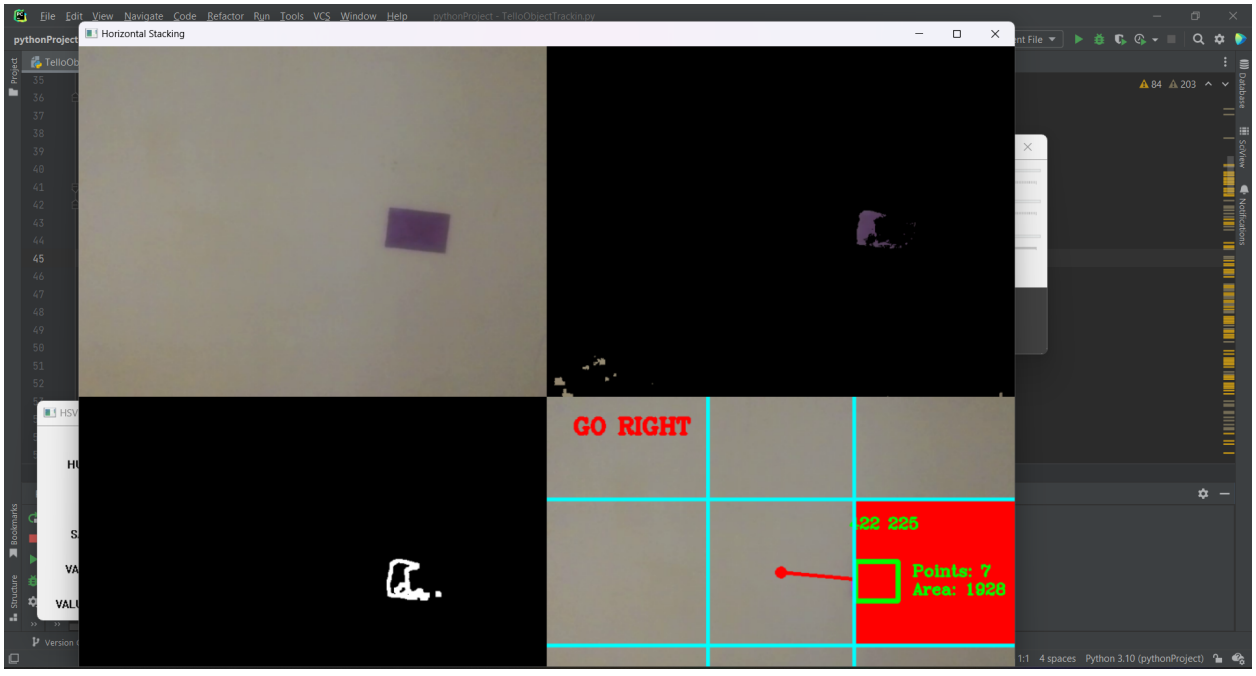


Figure20. Python outputs

6. WORK DONE FOR FINAL EVALUATION

- We are using the Tello drone in the Final Evaluation.
- It can be flown both through the app and commands.
- Python code for automated flying mode.
- It detects the object by Computer Vision(CV).
- follows the objects and reaches the nearest path to the object.
- And take photos and videos at that particular location.
- Optimizing CV (Computer Vision) model for object tracking
- Coding for giving instructions to ground level Actuators like pump motor etc..
- Optimized object detection and tracking.
- We have given a path to drone.
- Tello drone follows that path by using Python code.
- If anywhere drone misses its path it uses computer vision to correct its path.
- And by reaching the end of the path it collects data and passes it to the cloud.
- Front End, and Backend of the Website, Values will be updated on the website.

7. CONCLUSION

Operating the DJI Tello is an important first step to completing the goal for the tracking of an object. The keyboard commands help the user to place the drone where he or she prefers, (proper height, angle, distance from the object, etc.) in a ready position for tracking.

Once the DJI Tello can be controlled remotely, the next step to color tracking is to display the camera feed that the Tello sees on the computer using CV2. The pixels in the image can be searched for pixels of a certain color by analyzing RGB values. In this project, we used a range of blue values. The code will blur together pixels within the largest area of the violet color range and draw a boundary around the violet object we hope to track.

Tracking the object is done using a PID control loop incorporating the offset coordinates of the center of the object and the center of the frame. This is done by using the coordinates from the previous frame and comparing it to the current frame. These coordinate distances are computed in pixels. The goal of tracking is to track where the blue object is "now" based on where it was in the last frame.

The control loop uses the offset coordinates and the distance from the center to find velocities. These velocities are used to command the drone to move left, right, up, or down. It runs the loop for each frame and moves the drone accordingly. The drone should move either up, down, left, or right by observing the sign of the velocity in either the x or y direction. The velocity at which the drone moves is the magnitude of the value computed by the control loop. All of this should result in a drone tracking a violet object.

In this project, we proposed a method and built an IoT connection using autonomous UAV tracking and landing system that enables UAV tracking and the landing of a designated target in an environment with multiple interference targets. The image information transmitted by the camera was processed by Tello and coordinate transformation to obtain the spatial coordinate information of the specified target; then, the discrete PID control method was adopted to realize tracking and the landing of the UAV on the designated target. Extensive simulation experiments were conducted to evaluate the system's performance. The effectiveness and reliability of the algorithm and system were analyzed qualitatively and quantitatively with regard to various aspects, such as the target pixel coordinates, the position of the UAV relative to the target, and the tracking and landing process. The landing error of the UAV during the landing process after the target was stationary did not exceed 0.01 m. In addition, the advantages and disadvantages of the system were discussed at the level of both processor hardware and algorithm design, and corresponding suggestions were made for different problems.

Although drones are small in size and have restrictions on power, it is important to design an efficient algorithm for drone object detection. Variations viewpoint is another significant challenge to be addressed by the object detection algorithms. In future work, we can aim to investigate object detection using UAVs in agriculture applications. Precision agriculture deals to monitor the fields

precisely by collecting and analyzing the data. Acquiring aerial images using UAVs is less expensive than satellites. Object detection in UAV aerial images in precision farming is an important research area to be investigated. We proposed a secure onboard object detection framework in precision agriculture in this project and implementing it will be our future work.

8. FUTURE WORK

- Drone object detection has many applications in real time.
- We think that deep learning algorithms perform better than image processing methods.
- Although the drones are small in size and have restrictions in power, it is important to design an efficient deep learning algorithm for drone object detection.
- As future work, we can aim to investigate object detection using UAVs in various other fields.
- Precision agriculture is to monitor the fields precisely by collecting and analyzing the data.

9. List of Abbreviations

UAV = Unmanned Aerial Vehicle

CV = Computer Vision

DL = Deep Learning

RS = Remote Sensing

GPS = Global Positioning System

IMU = Inertial Measurement Unit

SPPNet = spatial pyramid pooling networks

RCNN = faster Region-Convolutional Neural Networks

SSD = Single-Shot multi-box Detector

ViT FRCNN = Vision Transformer Faster RCNN

FPN = Feature Pyramid Networks

SNIP = Scale Normalization for Image Pyramids

MBSSD = MultiBlock SSD

MQTT = Message Queuing Telemetry Transport

TCP/IP = Internet Protocol Suite

QoS = Quality of Service

TCP = Transmission Control Protocol

UDP = User Datagram Protocol

TLS = Transport Layer Security

10. ACKNOWLEDGMENTS

We would like to thank our mentor, Dr. Y. Raja Vara Prasad for guiding us in this project and providing inputs and suggestions during evaluations and working. All team members have contributed equally, sharing the workload since the beginning.

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