Unmanned Aerial Vehicle (UAV) for Farm Health Analysis

Project report submitted for

6th Semester Minor Project-II

in

Department of Electronics and Communication Engineering (ECE)

By,

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CERTIFICATE

This is to certify that the project titled Unmanned Aerial Vehicle (UAV) for Crop Health Monitoring” by “Akhil Kumar Donka, Jatin Aditya Reddy Seerapu, Sakshi Verma” has been carried out under my/our supervision and that this work has not been submitted elsewhere for a degree.

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July, 2020

Declaration

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Date: July 8, 2020

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UAV for Farm Health Analysis

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SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Sarmad Hameed, Imran Amin. "Detection of Weed and Wheat Using Image Processing", 2018 IEEE 5th International Conference on Engineering Technologies and Applied Sciences (ICETAS), 2018 Publication	1%
2	"Intelligent Systems and Applications", Springer Science and Business Media LLC, 2020 Publication	1%
3	Submitted to University of Sydney Student Paper	<1%
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Approval Sheet

This project report entitled "Unmanned Aerial Vehicle (UAV) for Crop Health Monitoring" by "Akhil Kumar Donka and Jatin Aditya Reddy Seerapu, Sakshi Verma" is approved for 6th Semester Minor Project.

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Abstract

Agriculture plays a vital role in Indian economy. It also contributes to our GDP, therefore to make a good profit and to get good quality crops we need to know about the infected crops and also about the weeds and insects around healthy crops to protect the healthy ones from being infected. The proposed solution incorporates this application of drones in the field of agriculture by using deep learning models to detect the weeds and insects around paddy crops. Unmanned Air Vehicle (UAV) is used for data acquisition of rice crop in different phases and states so that high quality of RGB images can be captured. Unmanned Air Vehicle (UAV) is used for data acquisition of rice crop in a village of Chhattisgarh state so that high quality of RGB images can be captured. The proposed method facilitates the detection of weed and insects from rice crop field using deep learning algorithm faster convolutional neural networks (Faster R-CNN_inception_resnet) it is implemented using Python3 with the help of Tensorflow API. The result shows that Faster R-CNN_inception_resnet method is the state of arts method for detection and classification of weed and insects with good accuracy rate. The information obtained from the processing is then relayed using a video transmitter that can send it to a user system located at a nearby location in real time using the concepts of Internet of Things. (IoT)

Keywords - Computer vision, Deep learning, Weed detection, Insects detection, Rice detection, Convolutional neural networks, Region based convolutional neural networks, IoT

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CHAPTER 1

Introduction

Paddy crops grained cereal food crops are grown under fertile soils with much input of fertilizers and pesticides. Hence, the need to develop technological tools to improve the management and productivity of the sector. A crop analysis system, when incorporated with beneficial features such as health monitoring, crop identification, etc. contributes to precision agriculture. The need for realizing precision agriculture is in large due to higher food requirements of the world in terms of quantity and quality. To have a product that can easily and accurately identify the healthy and unhealthy crops in a field, with autonomous flight capabilities, real-time computational features and is of low cost is greatly desirable. The increasing demand for improvising crop productivity has augmented the concept of precision agriculture, a system in which farmers optimize inputs such as water, fertilizers, etc. to get maximum yield.

Therefore an efficient mechanism is required to retrieve the information on the parameters which are hindering the growth of healthy plants, it will help in better growth of plants in the field. Moreover, the designed product should focus to cover large areas of land in less time, as it will be an added advantage in real-time implementation. The realization will help to obtain vital information about the field in less time, based on further analysis of retrieved data and also take necessary actions for restoring the plants' health or for maintaining its good health. Hence, such objectives can be fulfilled by aerial systems, because the aerial analysis is the appropriate way of surveying large sectors of fields in less time.

1.1 Problem statement

The need for a reliable and efficient crop analysis system has always been a necessity. In the present scenario a lot of chemical fertilizers are being used for betterment of crops and to increase their productivity to make a good amount of profit but in results we have increased the intake of chemicals in our diet. The farmers face a huge threat in every cultivating season from the unprecedented number of insects that might attack the crop plants. Also, it is to be noted at this juncture, that different class of insects require different types of pesticides to be rid of. This is usually done by farmers manually identifying crop to crop what kind of insects might be settling onto their crops and then purchasing the pesticides and spraying them plant to plant. The process is time consuming and requires a lot of man power, directly proportional to the area of farmland. Moreover, it is very possible to miss out a few sections or areas where there might be such insects, or contrary to this, it is also possible to end up spraying the pesticides at all parts of the field, where in reality this might not be required. Therefore, it is important to know the right places that require pesticides and of which type.

Another important parameter that has to be always kept in mind while developing such a complex integrated system that involves hardware build and a software compatible with the hardware is the product pricing. Most of the microprocessors associated with the aerial vehicle systems are expensive which results in high product prices. However, an important observation that has to be made with regard to these parts is their functionality, and in most cases, the makers purchase products that deliver to a lot of other functionalities compared to what is required and that is the key reason for such prices. An engineering solution that can cut down the prices by manifolds is always preferred over the existing solutions which makes it an additional on objective to the actual list of objectives associated with the making of such a product.

1.2 Internet of things and Deep Learning

Unmanned aerial vehicles are a choice of technology in several fields of work, such as construction, surveillance, photography, analytics, agriculture, etc. This project involves the use of an unmanned aerial system to solve the listed problems. The approach involves the simultaneous use of two existing technologies to identify the presence of insects and present this information to the user. The insects are identified with the help of a processing unit on the drone system and based on the feed (stream of live images) it receives by a stable camera, is processed and analysed for the presence of insects and of which type in specific. If present, the identified targets (insects) are bounded by boxes as per the developed program and is easy to view at the user end. The incorporated processing involves the use of the deep learning techniques that have been explained in detail. Deep Learning is a subset of Machine learning that involves the development and implementation of a processing algorithm that mimics the human mind and its thought process in the context of identification, recognition and such other tasks.

The processing is done on board and the information is transferred to the user and this involves the use of Internet of Things (IoT). In the development of such a tool, it has been constantly kept into consideration to manage and moderate the use of hardware technology that is needed, in order to make the product a subsequently low costing tool. This has been done keeping in mind of a potential product prospective that can be suitable in an agriculturally reliant country such as India. In the process of making a cost efficient product, a lot of problems arise with respect to the hardware build such as, the system stability, feed stability, flight time and processing power, etc. and has been elaborated in detail. The level of noise produced by the system has to be kept into consideration and a right combination of parts, flight motors, electronic speed controllers (ESC) and a flight controller has to be matched for pulse width modulation (PWM). Only then an electronically less noisy flying quad copter can be realised. The priority associated with making the drone less noisy is the fact that noisy combination of parts leads to system instability that is not visible to the user. However the vibrations produced as a result of mismatch, leads to a stuttered flight and the flight controller faces a task to address these oscillations in its flight which result in a distorted video feed. Such a feed is not suitable to identify physical objects let alone the tiny insects that harm the field crops. The feed is to be relayed in real time to an operating system at the user end so that the users can visualise the flight operation of the drone and also note the affected areas.

To devise such a product that can address the flight issues and also manage a successful image recognition at a price that is significantly lower than the industrial products is the challenge that has been attempted to be addressed in this project work.

CHAPTER 2

Existing Works

This section deals with the accounting of existing works into the field of precision agriculture with the use of unmanned aerial vehicles and use of systems for crop health monitoring [1]. Several researches have worked on devising UAV systems with autonomous flight as well as systems for crop health monitoring of the plants with the help of a micro-computer on-board UAV. An interesting work that has been the foundation for this project was the work on implementation of a low cost aerial vehicle for crop analysis in emerging countries [2], which is capable of providing unmanned flight for a drone as well as an image based processing system for crop health monitoring.

Also an important resource for our project has been the work on Plant health monitoring system using Raspberry Pi [3]. We have gone through several resources on drone operations, unmanned drone operations, raspberry pi based image processing[4][5][6], raspberry pi based crop health analysis systems, crop health analysis methodologies[7][8] and UAV systems for crop health analysis, based on which this project has been compiled.[9][10] Also, the use of Convolutional neural networks (CNN)[11] over the classical decision tress[12] give a better output in terms of accuracy in predicting what crop could an image taken from drone. Classical decision trees, have a lot of issues when it comes to memory management, computational aspects, and predicting the outputs, as compared to a CNN system, where the computations are done on a filtered image whose features are retained, apart from being a faster and precise methodology in predicting plants in a given image. The existing models have really contributed to the building of this project, where we were able to analyse the benefits and use the concepts associated for better results. [21] Presents a viable solution which optimises the predictions of insects and weeds versus the frames per second (FPS) in which it presents the results and processes the frames. A lot of solutions are posed by researchers all over the world but they face the same problem of a trade-off between making predictions and processing them.

The following table draws a contrast of work progress in the current research and to that compared to our work.

S No.	GPS Enabled	Crop Health Status	Vegetation Identification (Accuracy)
1[12]	Yes	N/A	N/A
2[5]	Yes	Yes *(NDVI)	N/A
3[6]	Yes	Yes *(NDVI)	N/A
4[7]	Yes	N/A	N/A
Previous system	Yes	Yes *(NDVI)	CNN (85%)
Present System	Yes	Yes *(NDVI)	R-CNN (88.5%)

Table 2.1 Contrasts in the existing journals

The above table shows the contrasts in some of the leading research works as compared to our work. The comparisons drawn show optimistic progress and improvements in our model as compared to these research papers. From the table, our work has detrimental impact in the sections involving the use of neural networks as well as crop identification, where we are able to provide results with high accuracy which can be used in real life scenarios.

The details of the work are in the subsequent chapters where every aspect has been covered in full length.

**NDVI: Normalized difference vegetation Index.* [1]

CHAPTER 3

Proposed Model

3.1 Introduction

To fulfil the objectives and aspirations by the unmanned aerial vehicle (UAV), the present system design incorporates use of the concept of Internet of Things (IoT) and Deep learning algorithms that help in the analytics. This chapter broadly elaborates the working and implementation of deep learning algorithms and specifically, the concept of convolutional object detection. The use of Internet of Things in our drone hardware build is presented as a separate chapter subsequently.

3.2 Deep learning

Deep learning (DL) comes under the broader family of machine learning and is similar with functionalities of the brain, called artificial neural networks. Also called hierarchical or deep structured learning, it works in layered architecture to find patterns in the dataset, thus giving more accurate results than machine learning algorithms. It is extensively used in fields like computer vision, audio recognition, speech recognition, medical image analysis, natural language processing, machine translation, bioinformatics, drug design, material inspection and many more. The primary motive of this work is to build a deeply convolutional neural network model in order to develop a weed and insect recognition system in Paddy crops.

3.3 Convolutional neural networks

Convolutional Neural Network (CNN) has numerous applications in the agricultural sector, as it could be helpful in increased productivity of crops by their proper maintenance. It also has the capability of predicting a plant disease at an early stage so that proper precautions could be taken. It helps in improved disease prediction that provides better productivity. It provides reduced agricultural costs so it’s affordable for a wider demographic.

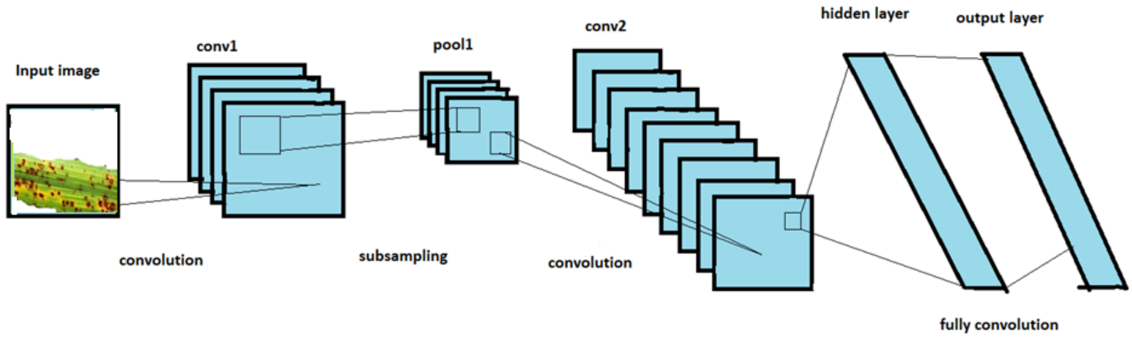

Figure 3.1 CNN Architecture

Convolution is a mathematical operation which is obtained by two functions f and g, which is the area of intersection of the functions. The calculation is given below.

$$z(t)def = f(t) * g(t) = \sum f(l) * g(t-l)\ l{=}\infty\ l{=}-\infty \quad \ldots\ldots.(1)$$

Integral form

$$z(t)def = f(t) * g(t) = \int f(l)g(t-l)\ \infty\ -\infty\ \ dl \ \ldots\ldots..(2)$$

In image processing images are in form of two dimensional spaces *f(x,y)* and the convolutional kernel also a two dimensional function *g(x,y)*, and the output featured image is as z(x,y) as given in equation (3).

$$z(x,y) = f(x,y) * g(x,y) \ \ldots\ldots.(3)$$

If the convolutional kernel is □ × □ is given, then

$$z(x,y) = \sum \sum f(t,h)\ g(x-t, y-h)\ t{=}n\ h{=}0\ t{=}m\ t{=}0 \ \ldots\ldots..(4)$$

3.4 The deep learning Model

This paper is proposing a deep learning model for detection of weeds and insects also classifying them in different categories using Faster R-CNN_inception_resnet model, which are mentioned below.

3.4.1 Flow of model

Model has been processed using captured dataset from the UAV. Below in figure... is the flow of processing of the deep learning model Faster R-CNN-inception-resnet.

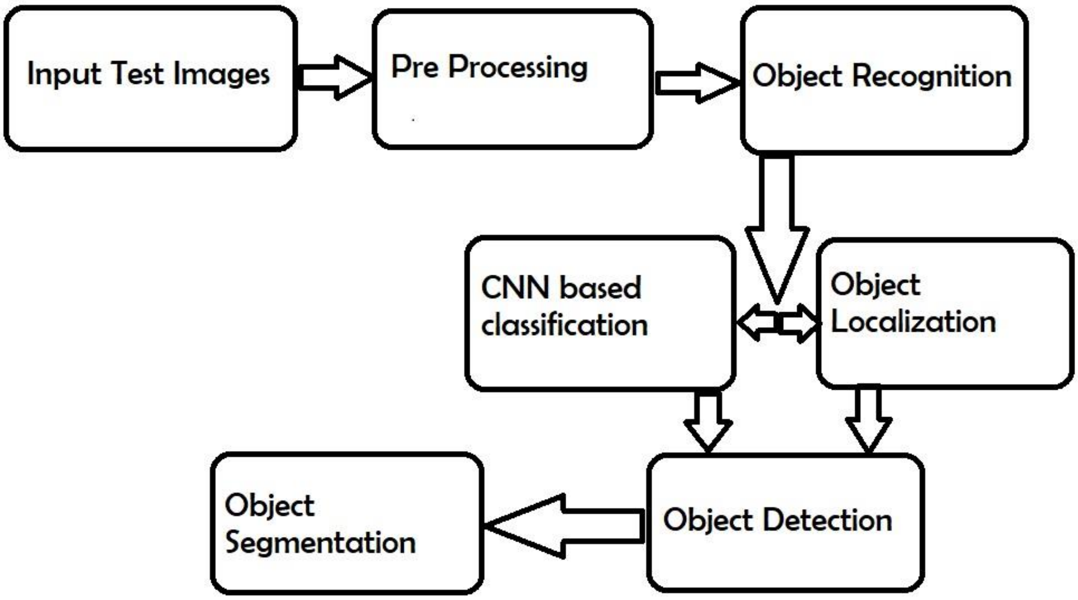

Figure 3.2 Flow of object detection

3.4.2 Image Acquisition

We have collected images of different fields. The insect dataset has 814 images in which 723 images are used for training and 91 for testing. There are fifteen categories of insects in the captured dataset.

Figure 3.3 Acquired images of insects

The weeds dataset has 224 images in which 194 images are used for training and 30 for testing. Below is the figure.. of some weed images which are further used for processing in object detection model.

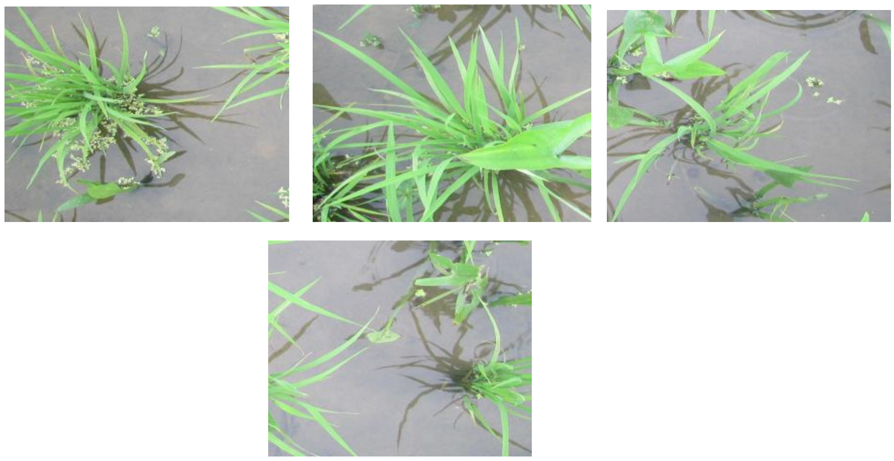

Figure 3.4 Acquired images of weeds

3.4.3 Data Augmentation

Since the dataset is collected manually,, the size of the dataset is very small (814+194 images). In order to get reliable results. There was a need to obtain a bigger set of images. In order to accomplish this task we took the help of augmentation technique. Different augmentation techniques such as horizontal and vertical shift, horizontal and vertical flips, random rotation are carried out to increase the number of images.

3.4.4 Faster R-CNN-inception-resnet

In the model, there are three parts of processing convolutional neural network, RPN and fully connected

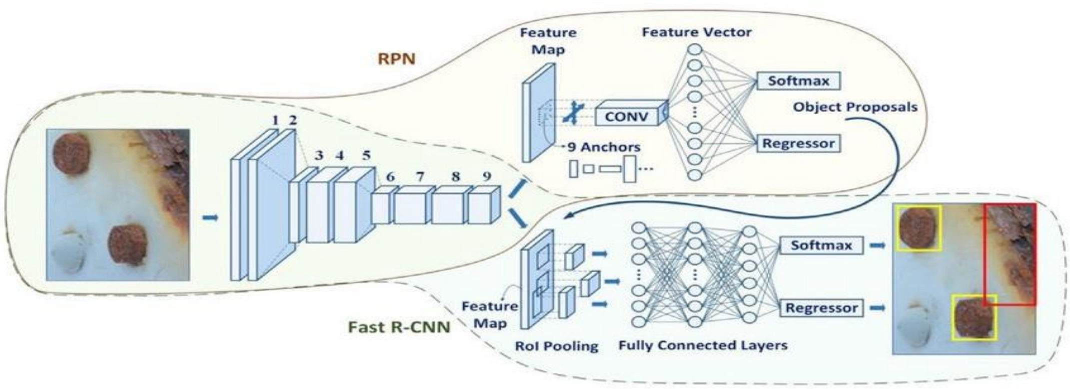

Figure 3.5 Faster R-CNN Inception resnet

CHAPTER 4

Enabling Internet of Things (IoT)

4.1 Camera Stability

For using our insect identification model developed in previous chapter, stable camera feed is a necessity in our application. Proposed UAV system consists of very noisy brushless motors and electronic speed controllers (ESCs). As we are trying to develop a low cost solution, instead of replacing all existing 4 motors and ESCs with costly ones, we can go for separate low cost embedded system – A gimbal. It is an electronic device that consists of an accelerometer and a gyroscope in certain designs that keeps its carrier, (camera in the case), stable and counteracts the movement of the system by making alterations in the opposite direction of the axis, making the camera stable enough to process a video feed. But before opting for this solution, proper vibration and noise analysis must be done to get an idea of gimbal parameter to be configured in future.

4.1.1 Vibration Analysis

The problem associated with vibration can be caused by the improper use of circuitry, i.e. motors, ESCs and the flight controller, or having incorrect PID values in the Gimbal. This causes minute but steady vibrations in the carrier, which results in a distorted video feed. Such a feed is not suitable for processing to identify insects or other objects. The developed system uses the Pixhawk flight controller, which provides the user with a software to track the presence of these vibrations in the system.

Flight Controller Pixhawk is equipped with accelerometer gives the vibration data of all 3 axis. These data is captured in flight log analysis file created at every flight and stored in flight controller memory. Once log file is ready, Fast Fourier Transform (FFT) analysis is done to get data of vibrations occurring at various frequency levels. The following figures show the vibration levels associated with our system before and after take off.

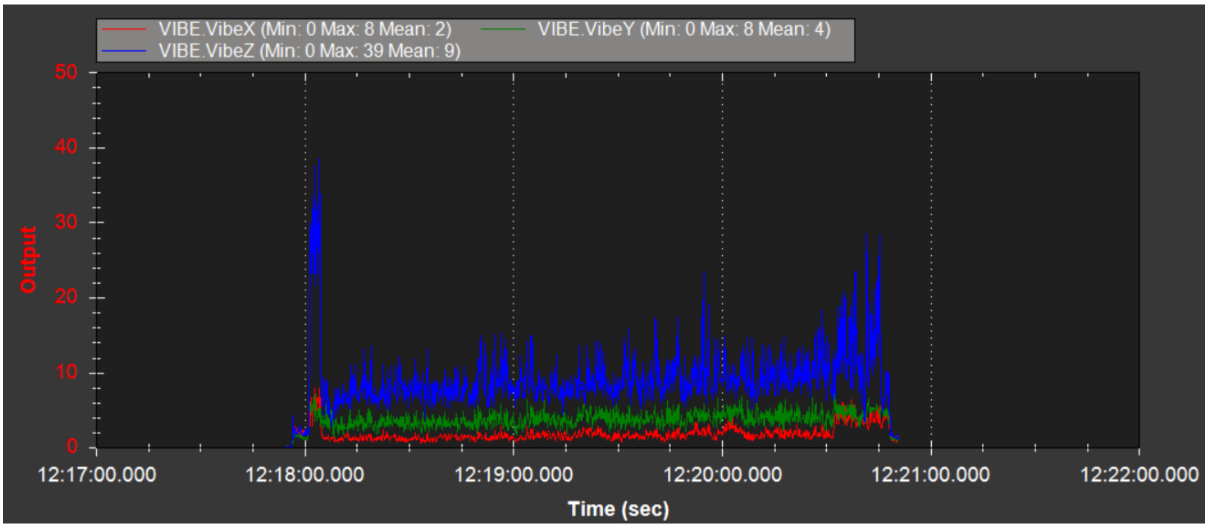

Fig 4.1 Vibration value before take-off

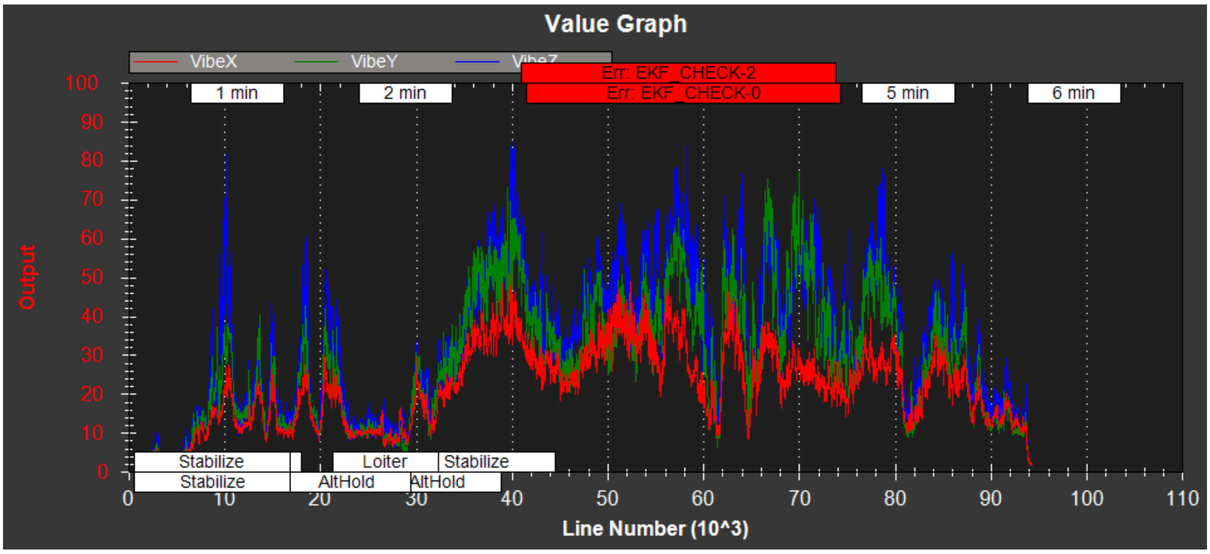

Fig 4.2 Vibration value after take-off

For a smooth video feed, the tolerable vibrations should be under output value of 50. If it is not, we then go for PID tuning further to get desired vibrational levels.

4.1.2 Gimbal and Camera System

For improved video stream stabilization, at an optimal price, the product uses a low cost 2 axis brushless gimbal which can be directly configured with the Pixhawk for camera 2 axis control when UAV is in mid-air. PID tuning is also necessary in this step if video turns out to be shaky or having distortions.

Fig 4.3 Two axis brushless gimbal

The system uses an inexpensive action camera placed on gimbal for testing purposes. The camera is connected to a video transmitter of 5.8 GHz which sends the stream in real time to receiver computer acting as ground station to UAV.

4.2 Internet of Things Unit

Pixhawk is developed as an open source project which can be controlled using inexpensive companion computers available in market today. Companion computers give access to real time flight logs of UAV system as well as its control which make the prototyping of any application easy. To make any robotics application ready to go market solution, every automation company today is going for Robot Operating System (ROS) in companion computers.

4.2.1 Companion Computer Setup & Enabling ROS

With future integration of sensors and cost factors taken into consideration, Raspberry Pi (RPi) suited to be best as companion computer. With ROS enabled in RPi, it is possible to create and handle stream of sensor data to get valuable insights related to agriculture. Pixhawk telemetry is connected to RPi serial pins, this gives access to real time flight sensor data e.g. Odometry, Accelerometer, live GPS coordinates, etc.

Camera placed on the gimbal can be connected to RPi which then gets feed on a ROS topic. This ROS topic is then accessed for computer vision applications in real time. To other pins available on RPi, we can integrate other sensors required for analysis. This whole needs to be connected to internet which will help us in getting field data anywhere in the world at any time. This is achieved using feature of tele-operation over the network in ROS environment. Drone access can also be configured where we can set permissions to a certain no. of users on controlling and getting data from UAV mid-air.

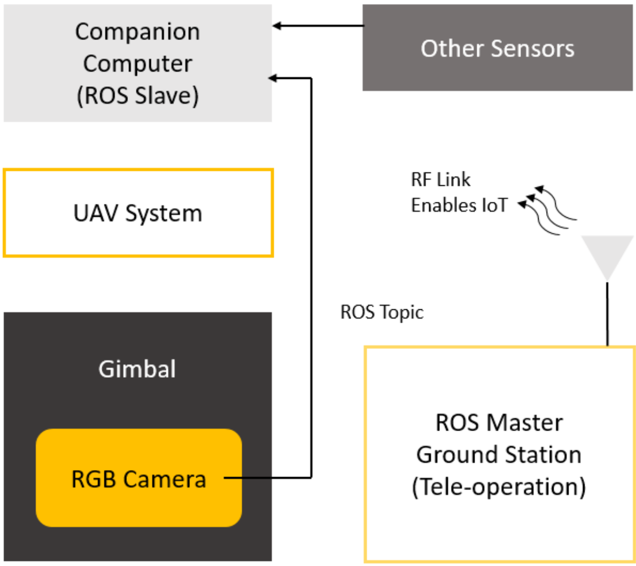

Fig 4.4 Proposed ROS integrated setup

4.2.2 Sensors for field analysis

Considering the fact that soil vitals such as temperature, humidity in ambient environment just above the crops will be same as that at the ground plane, we can equip our drone with necessary sensors to get soil insights. With sensors integrated into our UAV system, following analysis are done:

4.2.2.1 Field Orthomosaic

With images taken in certain time interval and their proper geo tagging, we stich images to create a map of the field where each pixel of the map contains the sensor information captured on corresponding geo location.

Fig 4.5 Orthomosaic Map of Survey Field

4.2.2.2 Crop NDVI

NDVI stands for Normalized Difference Vegetation Index. [1] It is the metric that is famously used to determine the health condition of a plant. The value should lie between 0.33 and 1 for a healthy plant. Generally with RPi on board, two camera setup in made for getting NDVI. In our case we are going for a single camera setup for making our IoT unit compact. In this setup, we remove IR Block filter from normal camera and put a super blue filter instead. This way NIR light is captured in Red channel of image and Blue channel captures visible light + little bit of NIR signal (negligible affect but a drawback). It is later then processed to get grayscale NDVI image and then finally we do color mapping to get better understanding. Results of this analysis are discussed in next chapter.

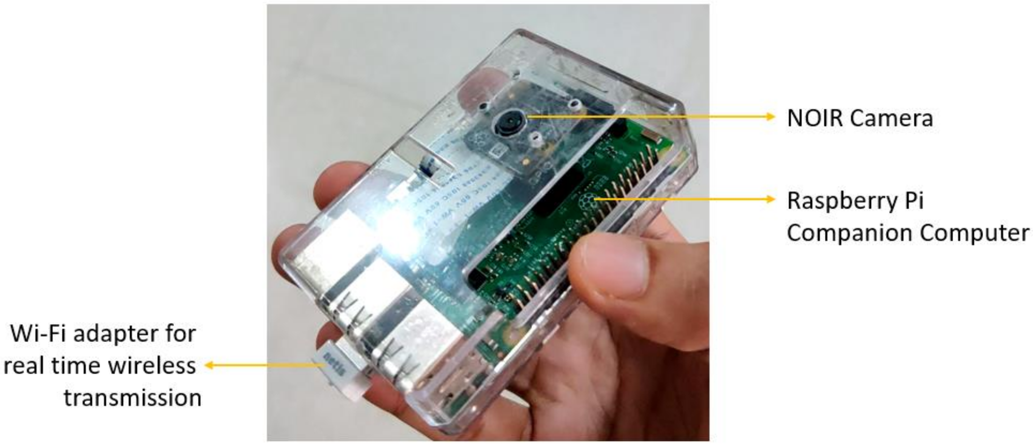

Fig 4.6 Glimpse of NOIR camera setup

4.2.2.3 Thermal Imaging

Being a catalyst in photosynthesis, soil temperature characteristics tell us a lot about biological process happening across the field. It stresses on the availability of nutrients for plant growth. An inexpensive DHT11 sensor (figure 4.7) is used in this work to capture temperature data.

4.2.2.4 Water stress analysis

Humidity is the perfect vital which tells about the amount of water content in ambient environment. DHT11 sensor which is used for thermal analysis is also used for capturing humidity related data. Sensor capturing humidity value along with the GPS coordinates can be mapped onto orthomosaic generated and with further color mapping gives better visualization of water stress points on the field.

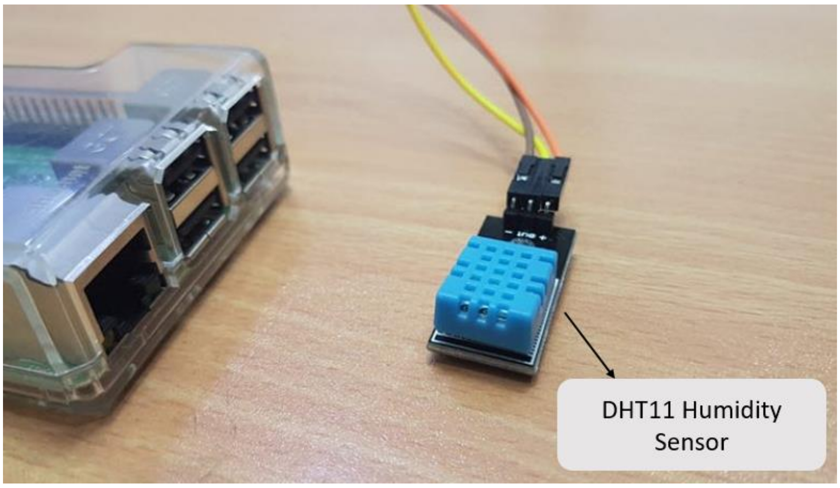

Fig 4.7 Humidity Sensor Setup (Also calculates temperature)

4.2.2.5 Insect Identification using computer vision

With neural network model ready mentioned in previous chapter, we apply this model on our real time feed coming on a ROS topic. We created ROS node for achieving this task, this node is started on our ground station which is connected over the internet to our UAV system for getting data. Using OpenCV, the identified locations of insects are plotted on image frames. These images are also geo tagged to identify the precise location of insect on field.

The above mentioned features are incorporated in the present system, along with an improvised identification deep learning technique whose results have proven to be an improvement compared to the previous results.

CHAPTER 5

Results and Discussion

For getting NDVI analysis and clear visualization on monitoring plant health, a python based flask server application is setup. It sends its real time video feed and NDVI processed stream to its local IP address on a specified port. This also serves as creating farmer ready easy to use interface for our application. The grayscale images are mapped into coloured ones which gives a more clear analysis. Blue coloured pixels shows the areas of either no vegetation or plants with very low photosynthetic levels. Other photosynthetic levels are displayed using red, yellow and green colours which show, unhealthy, moderate health and healthy plants.

Such an interface can be viewed both in a desktop or a smart phone browser. The system is tested in indoor conditions and ready to be deployed on real plants in field. However, field tests haven’t been executed due to the present pandemic situation. Therefore, the complete system test hasn’t been verified however with individual functionalities of the system have been checked and verified to be functioning successfully.

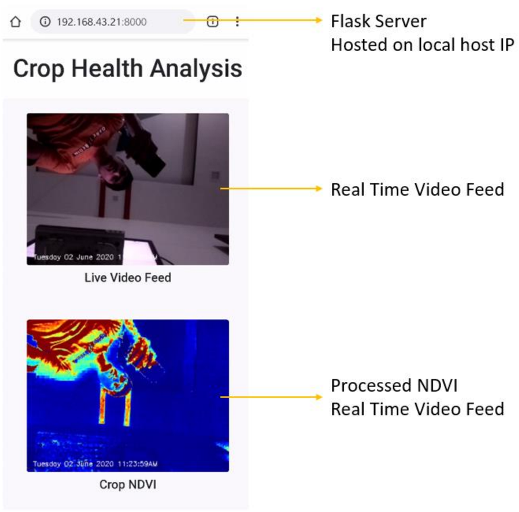

Figure 5.1 NDVI feed from the camera.

A similar work has been previously developed using the CNN model in an earlier made project. The described project uses the concept of R-CNN model, which brings improvised results in both insect and weed identification bettering earlier results.

Various metrics are used to evaluate the performance of the models. At the time of training, training accuracy and loss as well as validation accuracy and loss were calculated after each epoch. The model accuracy has also been calculated which the ratio of no of accurately labelled images and total number of images in the database , the accuracy as well as time elapsed of Faster R-CNN-inception-resnet is good and giving a very decent average accuracy of 88.5% for insects and 78% for weeds. The training accuracy and validation accuracy is calculated over these images.

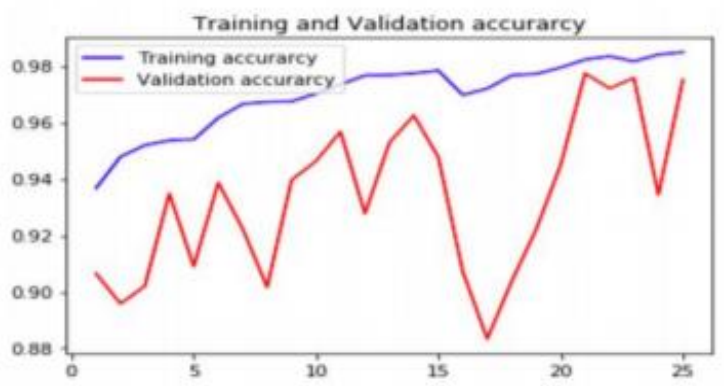

Figure 5.2 Training and Validation accuracy

Figure 5.3 Training and Validation loss

The paper has shown how the system trained on acquired dataset, and the output result is shown in figure 5.4

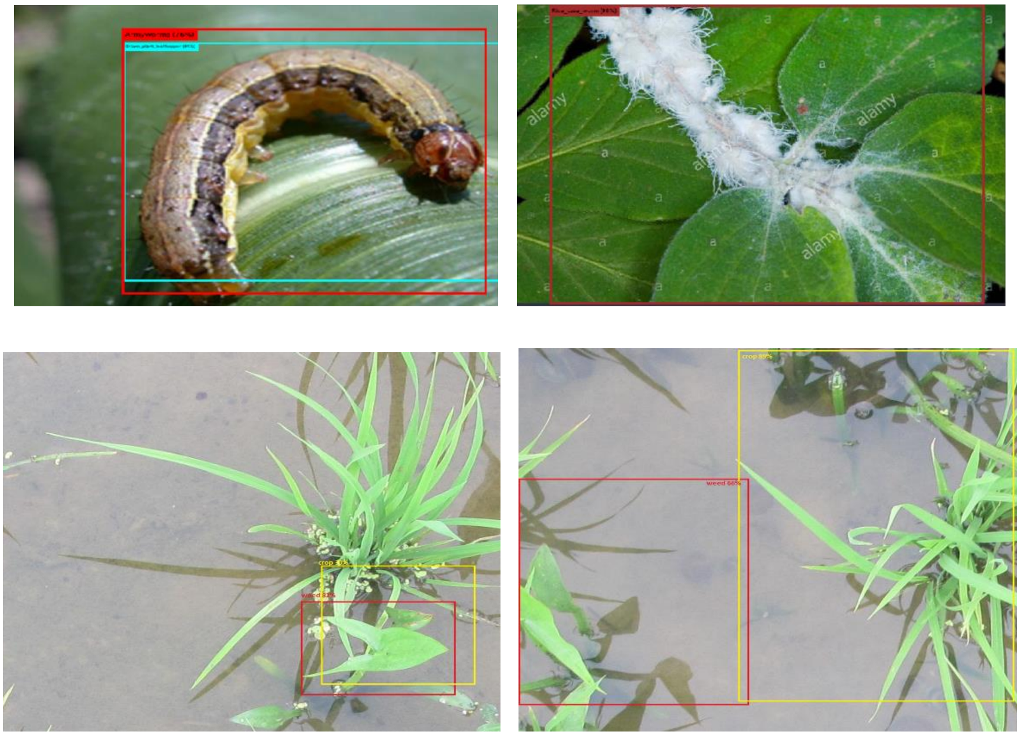

Figure 5.4 Insects and weeds classification and detection

Authors [21] have previously worked with a combination of other available deep learning feature extractors and detection algorithms. Based on their results we have compared our proposed deep learning model in terms of mean average precision (mAP). Comparing the two stage deep learning architectures where the first stage is to get object boxes and second stage is to classify the objects, when it comes for insect identification our model outperformed the existing ones based on Faster RCNN by 4% more accuracy. But here trade-off happened in terms of frames per second (FPS) of predictions. Being more accurate and consuming more resources, time of making predictions fell drastically. These include Faster RCNN, Resnet, etc.

On the other hand, single stage detection algorithms which have less complexity and resource consumption give a higher frame rate of predictions with a trade-off in terms of accuracy. These include Single Shot Detectors, Yolo v2 & v3, Receptive Field Block network (RFB) etc.

Classifier	Faster RCNN	SSD	RFB	Yolo v3	Faster RCNN
Detector	VGG16	VGG16	VGG19	Darknet-19	Inception + Resnet
mAP	83.53	86.19	85.23	86.1	88.5
FPS	13	46	80	67	22

Table 5.1 Comparative analysis of existing models Vs our model

CHAPTER 6

Conclusion

The developed project presents an engineering solution to identify insects and weeds growing in field and provide this information to the users without actually having to pilot the drone either. Such an analytics tool can prove beneficial to the farmers and with a significantly lower product cost, the proposed solution stands as a good market alternative. In future, an attempt to fine-tune the prediction model will be made and also hardware verification in the form of actual flight tests can be conducted subject to the pandemic situation. Bringing visual colors to the health status calculating program for plants using NDVI acts as a better presenting tool for farmers to visualise their crops and their health status in a broader perspective. The intelligent use of IoT enables the drone to communicate with users. The potential in the buzzing field of internet of things, is endless and for example has the potential to communicate with swarm of such drone systems. A seamless opportunity lies in front of the success of this aerial crop health monitoring system. In this work, we have successfully evaluated the involvement and use of Internet of things (IoT), with our software. The health status in terms of image recognition using NDVI has been color mapped to representative colors that indicate the health status with better clarity. In the quest to implement the best solution in order to identify insects and weeds, we come across the practical constraints are well illustrated in Table 5.1, as there’s a trade-off between the presented frames per second (FPS) of predictions and the model accuracy. In this work, we have examined the use of R-CNN and compared it to the results of four other existing algorithms. While each of them have posed the compromise of accuracy to the presented frames per second, the inaccuracy is forgivable. In future, we aim to study further models that use lesser resources and provide a means to optimize the scenario in the best possible way.

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