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# Drone-based Detection and Geo-Mapping of Wastes, Weeds and Diseases in Plants using Deep Learning

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***Abstract*—It has been recognised in recent years how detrimental pollution has been to the environment, as evidenced by global warming and a decline in the standard of living in developing nations. When it comes to pollution, plastic pollution is one of the most serious issues that humanity has created. Apart from the fact that plastics are non-biodegradable, they also reduce plant yields and deplete soil fertility. To avoid this situation, waste management education is required. It is critical to eliminate these contaminants prior to their ability to seep deeply into the soil. Weeds are unwelcome plants that grow in close proximity to other plants. They not only supplant healthy plants in terms of development, but also feed on them, robbing them of nutrients and resulting in a significant decrease in agricultural production. Another factor complicating agricultural production is the presence of plant diseases. Scientists are engaged in a variety of endeavours, including forecasting illnesses, predicting their potential, and identifying diseases before they become fatal.**

**Our new method employs a first-of-its-kind strategy that involves mapping a region using a drone's vector and then detecting map errors using the UDP stream from the drone's camera, a first in the industry. This data is analysed in real time using Nvidia Deep Stream. To train our data-set, we will use a custom-built Sequential Convolution Neural Network.**

***Index Terms*—Drone, Plant Disease, Weeds, Nvidia, Jetson Nano, CNN, Artificial Intelligence, Deep Learning, Wastes Detection, Tensorflow, UAV**

## I. Introduction

The current century has seen a rapid growth in the field of Automation and Technology. We humans continue to explore the deepest areas and are striving to develop products that can benefit and provide comfort. While technologies are something that all of us depend on in our day to day lives, there are a few things that have not changed ever since the beginning of humanity - things such as Food and Cultivation. Food is essential to live. And the ever-increasing population and the decrease in cultivatable land calls us for a urgent look into ways be which we can improve the agricultural sector. Millions of people starve everyday for this basic commodity and what best use can technology be of if it isn't able to provide the primary essential for existing for humans.

Plants, it should be emphasized, play an important role in the natural cycle of life on the planet. Due to the fact that they offer both food and oxygen, they are necessary for the survival of all creatures. In order to meet the needs of a growing population in the existing environment, food production must be increased. Agriculture is the most important source of food production, yet weeds are becoming a major source of concern for farmers as they cultivate their crops and gather their harvest.

The primary issue arising in the current society are the dearth in usage of technology in the field of Agriculture [1]. Immense advancements can be bought upon the methodology of cultivation to make work faster, easier and safer for the farmers involved in growing them. Cultivatable land is decreasing year by year because of the damage done by our species. The increase in population and the decrease in the amount of crops grown substantially increases the demand and the price of the goods, making it harder for the lower sectors to afford food [2]. Not to mention the spike in inflation which makes it even harder to afford them.

One way to lessen the burden on the farmers and provide the food on a substantially cheaper price to the general public is by increasing the crop yield. While it is easy to make more cultivatable land, it is smarter to innovate and bring in technologies which can improve the overall crop output efficiency. Over 20 billion pounds of crop yields are wasted every single year where factors such as Weeds, Diseases, Inefficient Agriculture, Water Content and Soil Nourishment are some of the main factors for the same [3].

Our goal through this research is to improve the overall efficiency of the crop yield by Detecting and Analysing the:

- Unwanted weeds growing around near the cultivated plants
- Plastic and Non-Biodegradable Wastes thrown around in the field
- Type of Plant Diseases based on it's leaf's characteristics

Using Unmanned Aerial Vehicles (drones) in conjunction with Integrated Weed Treatment (IWM) allows for more targeted weed management at specific locations. This type of weed management is both successful and good to the environment at the same time [4]. For example, combining drone picture collection with further processing utilising machine learning techniques can be utilised to find weed growth regions in a field [5].

In this paper, we will be developing and looking into how we can utilise technology to overcome the above issues.

## II. Objectives

### A. Preliminary Analysis of Current Trend

The farming cultures practiced today are mostly methods that were derived centuries ago. While those methods might have been beneficial for crop cultivation in the past, the current trends, atmospheric changes and the lifestyle has changed it drastically. With overgrowing of plants, comes weeds and carelessness of humans comes wastes in soil.

Weeds are one of agriculture's most harmful abiotic components, causing significant productivity losses all over the world. They suffocate crop growth by competing directly with resources including light, space, soil moisture, and/or nutrients. They are also one of the most difficult ones to control. Around 14% of the total wastage in consumable foods is caused because of the damage done to crops by weeds. India has lost agricultural output of more than $10,000 million, according to figures from the Agriculture Ministry, which is more than the total projected allocation for agriculture at the Centre for the previous fiscal year [6].

Wheat, rice, peanut, and soya-bean crops are all affected by the presence of such weeds. They deplete soil nutrients and moisture directly, and they compete with agricultural plants for light and space, lowering crop yields. Indirectly, they harm crops that harbour pests and disease agents [2]. It is necessary to develop a new method of differentiating crops in order to achieve the best possible outcomes for a variety of reasons, including but not limited to: lowering agricultural costs, automatically removing weeds from within crops, spraying infected crops with the appropriate chemicals, and so on.

Urbanization has caused in the production of too much of non-biodegradable products and more often, they are thrown away carelessly into healthy soil and such wastes completely spoil the richness and value of the soil. While educating people not to litter is one way, removal of present wastes, if any, is essential too.

The increase in temperature due to Global Warming is one such reason as to why Plant Pathogens and Diseases have been thriving recently. Global warming is relatively new, and primarily because of our own mistakes [7]. Thus, intervening and adjusting the growth of plants is essential. These diseases are quick and hard to be detected by a novice. And once the disease pop up, it quickly spreads across the whole plantation, if left unchecked. It has become a tiring and prioritized task for farmers to make sure that there aren't any diseases spreading around.

### B. Proposed Solution and Technological Improvisations

Developing and training proprietary Deep Learning models to detect the above mentioned cases. But, in order to deliver these models to the end user, as user-friendly as possible, we will be developing and using a semi-autonomous drone to get the image/video feed. This makes the trained CNN models deliverable to end-user and also does the work quicker and easier. Drone is a relatively new technology which has the scope to be used in a lot of domains and we believe tapping it's potential to improve crop yields would be highly beneficial.

Fig. 1. Picture of the Drone that was used during research

The proposed drone system is integrated with a 720p HD camera with stabilization and UDP stream which significantly reduces power consumption. The low power consumption increases the flight time to 15 minutes.The drone can be operated in autonomous and in manual mode. In autonomous, the drone can fly on its own which includes landing and take-off. In case of a malfunction the drone can be switched back to manual mode instantly to avoid any accidents. The custom model created using Tensorflow's Keras API coupled with implementation's of LSTM(Long Short-Term Memory),droppings and 2D Convolutions gives the best performance. It is of great help in many challenging situations during weed detection, such as capturing images of crops for signs of weed growth under different lighting conditions, data acquisition when changes occur in the plants colour and shape as they grow.

Computer vision techniques such as image processing and machine learning are used in concert with each other to classify distinct plant genera. This eliminates the difficulties that novices experience when it comes to identifying plants. Typically, plant classification is based on the properties of the leaves. There are several reasons for this, including the fact

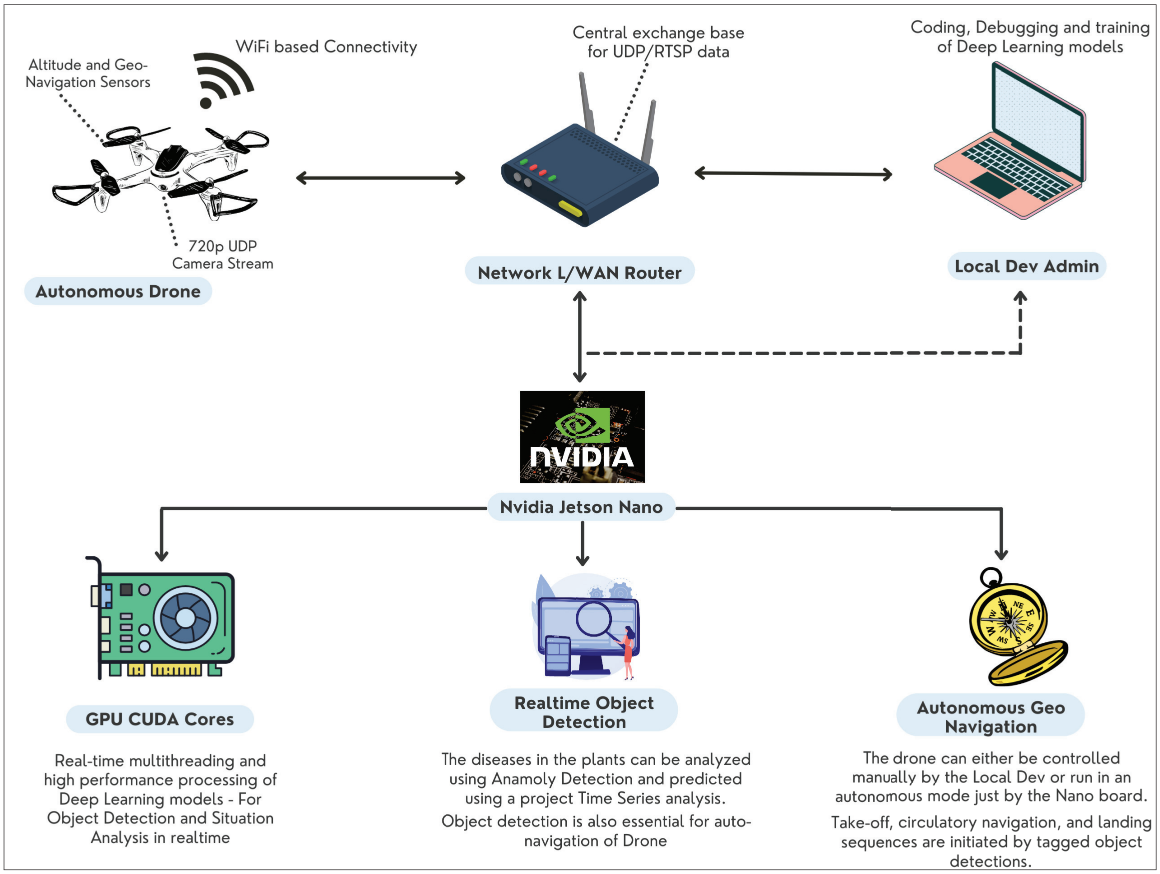


Fig. 2. Diagrammatic representation of the flow of data and task compute

that leaves are easier to inspect than flowers due to their 2D shape as opposed to the 3D shape of flowers, and the fact that leaves can be found throughout the year as opposed to flowers, which only develop during the blooming season [8].

The drone is semi automatised to create it's own dynamic path by detecting the presence of "key" objects and moving to that location. And as it moves, it send the UDP stream from the camera to the central server [9]. The CNN DL models present here check for the various topics discussed above, and if any/all of the wastes, diseases or weeds are detected, the location is Geo-tagged for human intervention.

The strategy of integrating Deep Learning with a Drone would not only aid in the identification of such diseases and wastes much more quickly than previously, but it will also aid in the mapping of the precision of their location, which may be used for further autonomous works [10]. When we imagine a world of automation, it is vital for all of the applications from diverse sectors to function together, which is why we feel that the tagging of wastes would be of great help to land-based waste-pickers and agricultural cultivators.

## III. Design and Development

### A. Project Planning and Timeline

We completed the roll out in approximately three months. The first month was spent conducting a literature review and developing a proposal. We needed to ensure that we have the appropriate Data set accessible for training our models. Otherwise, we will have to construct a data-set on our own.

After the same, we had a bunch of other tasks to focus on

- Deciding the training Params
- Understand the Pipeline flow for the Proposed Deep Learning Model
- Debate on implementation of Time Series Analysis and Anomaly Detection
- Communication with the Drone
- Stabilizing the Drone
- Live Interrupted UDP Transmission of Video from the drone while flying
- Implementing a real-time analysis of the streamed video to fetch the data that we are searching for in the video through the previously created CNN Pipeline model

### B. Datasets

Since the project requires three different Custom Models trained, we use various methods and implementations. Firstly, to develop the Plant Disease Classifier Model, a sophisticated 27 layered model was developed using a pre-annotated dataset containing the diseases and the name of those plants [11]. This data set contains 39 distinct kinds of plant leaf and background photos. There are 61,486 pictures in this data set.

We increased the size of the data set using six distinct augmentation approaches. Image flipping, Gamma correction, noise injection, PCA colour augmentation, rotation, and scaling are the techniques used [12].

A similar dataset containing of plastic bottles and other non-biodegradable items were taken and a model was derived. It is necessary to derive these models separately in different models so that the frames could be passed for the detection as per our need and then the output can be merged and then sent back.

### C. Pipeline of the Deep Learning Model

We used our custom designed Deep Learning model trained using multiple Hidden Layers using Tensorflow and PyTorch. The data was split accordingly to The models were trained using T4 GPU's and the params were constant varied until the result was not over fitted while satisfactory accuracy was seen with the validation data. Cloud GPU's used for the initial training of the models in order to speed up the process [13].

The models had the inputs as images and the output was related to the detection. The input image was made sure to follow the dimensions that are compatible with that of the camera in the drone so that they can work with the live data directly without much conversion.

Image Augmentation was implemented to utilize the image data sets to the maximum. This also ensured that the model would perform during real life scenarios. While the input feed is sent from any drone, it can be seen that they images would not be sent in a flat way. It is essential to have the flexibility to detect the diseases from varied angles and this allows us to do the same [14].

The trained models as saved as a h5 file. This allows to easily use the trained model along with the code developed for the drone. A h5 file saves the user time and resources as they would not have to train a new model every time the drone is deployed. Instead the pre-trained model can be reloaded very quickly and the outputs can be derived from it.

### D. Communication and Stabilization the Drone

To demonstrate the possibility of utilizing a drone semi-autonomously to detect the diseases and weeds, we are using an actual programmable drone - DJI Tello. While there are libraries to help us to connect to the Drone to send basic functions, there aren't any pre-defined functions to help us implement Artificial Intelligence. Python has been utilised to develop and code the complete program (Version 2.5.x - 3.6.x).

After the initialization of the libraries, focus was shown on the initial communication with the drone. Many of the supporting libraries were not compatible with Windows, hence alternative arrangements and rewriting of the code was done. Functions were implemented for all the General functions such as Takeoff, Land, Movement, Rotations, etc. The functions can then be later called in another program when needed and the drone would respond automatically. Essential edge cases for fall detection, minimum stationary height, top speed and altitude [15].

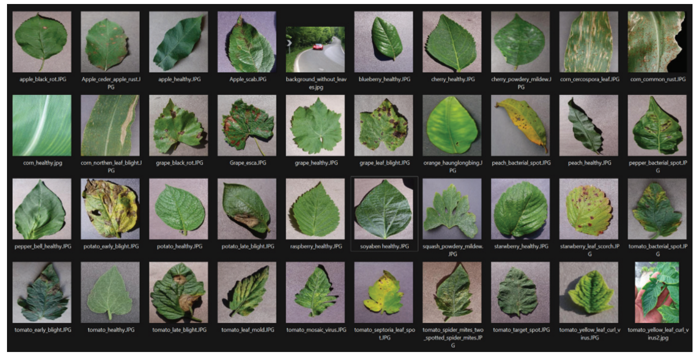

Fig. 3. Snapshot of Data-set for Identification of Plant Leaf Diseases

```
CNN(
  (conv_layers): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU()
    (2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (3): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): ReLU()
    (5): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (7): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU()
    (9): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (10): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU()
    (12): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (13): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (14): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU()
    (16): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (17): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU()
    (19): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (20): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (21): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU()
    (23): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (24): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU()
    (26): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (27): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (dense_layers): Sequential(
    (0): Dropout(p=0.4, inplace=False)
    (1): Linear(in_features=50176, out_features=1024, bias=True)
    (2): ReLU()
    (3): Dropout(p=0.4, inplace=False)
    (4): Linear(in_features=1024, out_features=39, bias=True)
  )
)
```

Fig. 4. Info of the Convolution & Dense Layers used to train the model

Since the drone was completely controlled manually by the Python Program, this also meant that the Auto-Stabilization is not as effective as when flown normally. Thus, based on the moment of the position of the Drone and it's change in altitude, the RPM of the motors can be indirectly altered by varying the voltage sent to the motors. This will in-turn reduce or increase the speed of that particular propeller and the drone would be stable. Note that this case is rare and is good to implement only when the surroundings are windy.

### E. UDP Video Feed Pre-Processing

The Device which hosts the program is connected to the Drone through a separate Wi-Fi connection. This allows communication between the host and the drone using the WiFi protocols. The data is sent from the drone using UDP so that, even if some of the packets or frames are lost, the drone is in continuous sync with the host and it is able to respond to the commands quickly without any delay. Initial studies show that converting UDP to RTSP (Real Time Streaming Protocol) is of a better option than working on the frame as received. Although initial development was made using RTSP, the code was then shifted back to utilise UDP as it felt more simpler and comfortable to work with [16].

Thus, once the drone boots and connects to the program running at host, it starts sending a continuous stream of video feed, The video stream is at a appreciatively 24 fps at its best. The input stream is then received as frames by openCV [17]. openCV allows the performing of various data manipulation functions as ease. The frames are cropped as per out requirement and then optimised to improve the overall quality of the details in the image.

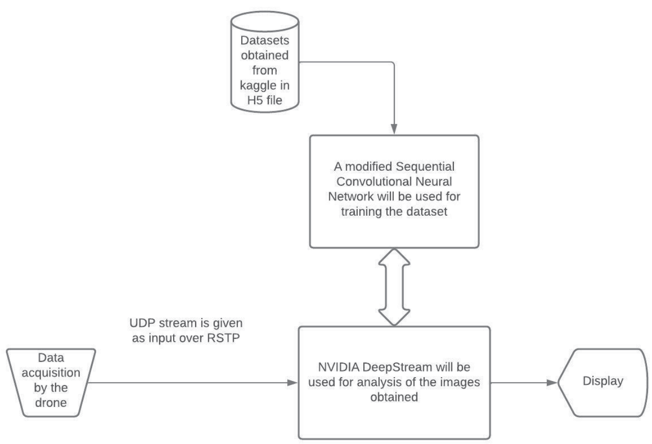


Fig. 5. Workflow representation of the CV & Tensorflow H5 models

The previously defined and developed models are then passed through the pre-processed frame. But, since the trained models are advanced classifiers of a single domain only, we will need another general classifier - A general object detecting model that can help s in selecting the classes before the frame is passed to the other models. MobNetSSD Model - A pre trained object detection model is utilised for detecting the basic classes [18] [19]. If a plant or object is detected in this object classifier, only then is the detected general object sent to the other model for further analysis.

This is a highly efficient method since, by this way, we will not be running all the models every time. The precision detection models are run only when a related class is detected in the frame. Detecting the classes (such as "Plants" or "Table") provides us the bounding boxes before hand, and this also allows us to easily send only that specific part to the detection models which we obtained while developing the pipeline before. The findings are then obtained from the models. The findings are the selected using a bounding box and then marked [20].

If any of the issues/diseases are found, the Geo-Location of the drone along with the finding description is saved in the database. This will prove helpful to the farmers as they will have to concentrate only at those places instead of the whole land.

## IV. Implementation

### A. Flight methodology

1) Automatic Flight Mode: One of our main objectives in this implementation is the automation of drone traversal. We are going to be using a DJI Tello drone that has been stabilized for the project implementation. Since a DJI Tello is not embedded with a in built GPS we are going to use spoof GPS for the mapping process. The takeoff, traversal and the landing of the drone is automated using OpenCV deep learning module with MobileNet SSD Caffenet for object detection. Using the Tello SDK User Guide, as soon as the ML model detects a specified object in the input Tello video stream, it will send the Tello a command. The model uses the following object classes: background, airplane, bicycle, bird, boat, bottle, bus, car, cat, chair, cow, dining table, dog, horse, motorbike, person, potted plant, sheep, sofa, train, TV monitor.

On detecting any of these aforementioned objects the drone will initiate an obstacle course and take off from its current position. Beyond this the drone is programmed to send a video stream to the Jetson Nano where a custom model will be used to determine whether the crops have weed growth/diseases.

### B. Video Capturing and Streaming

1) Video Capturing: The DJI Tello comes with an integrated 720p HD camera which resourceful and efficient in carrying out all its functionalities i.e. video streaming, object detection. The maximum speed is of the drone is 8m/s and the maximum flight height is 30m, this helps in acquiring data throughout a large area. The camera is stabilized and the data obtained through it does not contain loss due to destabilization. A live UDP stream can be obtained from it which is necessary for real time object detection.

Fig. 6. Live UDP feed received from Drone while on air

2) Video Streaming: During its course, the drone captures the video steadily and sends it to the Router. Ideally the video stream is sent to a connected network server, but a router is easy to configure and is better for mass production than that of

a network server. The process of weed detection and disease detection in crops should occur in real time hence we prefer UDP over any other method of streaming so that the video feed is real-time, even if there are any interference/packet loss. Once the video is streamed, the same is received by the device. The UDP stream is changed to an RTSP(Real Time Streaming Protocol) stream so that we will be able to work along with the video stream more flexibly and improve computing speed as well as the accuracy

### *C. Video Stream Processing and analytics*

1) MobileNet SSD Caffenet: Open CV is a deep learning module used for image and video processing. We are going to couple it with MobileNet SSD Caffenet for detection of objects. MobileNet is a type of convolutional neural network created specifically for mobile and embedded vision applications. When compared to a network with normal convolutions of the same depth in the nets, MobileNet uses depth wise separable convolutions, which reduces the number of parameters dramatically. As a result, lightweight deep neural networks are created. SSD which is Single Shot Detector is used to detect multiple objects from a single shot in an image. The drone is capable of discovering 16 different types of things in real time. The stabilized drone will takeoff from its current location if it detects any one of the objects that have been mentioned in the flight methodology section. If the drone detects a person it will stop its circulatory navigation clockwise at 45 degrees and will land automatically. Till a person is detected the circulatory motion in clockwise orientation will continue [21].

2) NVIDIA Deepstream on Jetson Nano: NVIDIA Deepstream Software Development Kit is a AI framework that will be used for the video Stream analytics . It can be used to build end to end AI powered applications used for video and sensor data analysis. In our implementation the SDK will be used to for analytics and alerts with respect to weed growth in crops or signs of diseases that manifest as scab on apples, common rust in corn leaves. Deepstream offers support to SSD(Single Shot Detector) which is an object detection model that we have used in our project that will assist us in detecting multiple objects in a single image [22]. But all the tools and functionalities provided by NVIDIA Deepstream cannot be applied to the their maximum potential without the hardware and architecture provided by the Jetson Nano. The Jetson Nano is a powerful computer that is capable of running multiple neural network in parallel for object detection, segmentation and video stream analytics. NVIDIA Deepstream working in tandem with Jetson Nano provided us with a reliable and accurate analytics [23].

### *D. Custom Model for Weed/Disease detection and Waste Detection*

A dataset containing 39 distinct types of plants and backdrop photos was used to create a bespoke model for detecting illnesses in plants.Augmentation procedures can be used to expand the dataset's size. Data augmentation is a set of techniques/processes that help to artificially increase the size of datasets by adding new data points to existing ones. All of the photos in the dataset have been annotated on a variety of factors, ranging from the type of diseased leaf to the disease that has afflicted the plant/crop [24]. The dataset also includes sample data of healthy plants indicated by their leaves. A model with 27 layers was developed using this dataset of 61,486 images. A similar dataset that includes photos of plastic accessories such as bottles and bags, as well as different non-biodegradable components is used for the waste detection model [25]. The layers in the custom model is a combination of convolutional layers and dense layers. Because it employs a filter to convolution operations by compelling input values to share the parameters, the convolutional layers contain fewer parameters. The dense layers take a radically different approach by employing a liner operation, in which the function forms each output dependent on each input.This resulted in obtaining good accuracy in predictions. A T4 GPU was used to run the custom model for 5 epochs and there is a gradual decrease in the train loss and validation loss with the increase in the number of epochs, indicating the decrease in the loss function while the training data and validation data is used respectively.

## V. Results and Discussions

The proposed project intends to provide a framework for detecting weeds and diseases in plants. Extended functionality is the detection of waste discarded in various national parks or areas where it can cause harm to the soil or the local flora and fauna.

By successfully recognizing either weed growth or diseases on plants in real-time the affected plants can be mapped quickly and efficiently. With this accurate plotting of affected plants help can be administered to them and the yield obtained will be significantly higher.

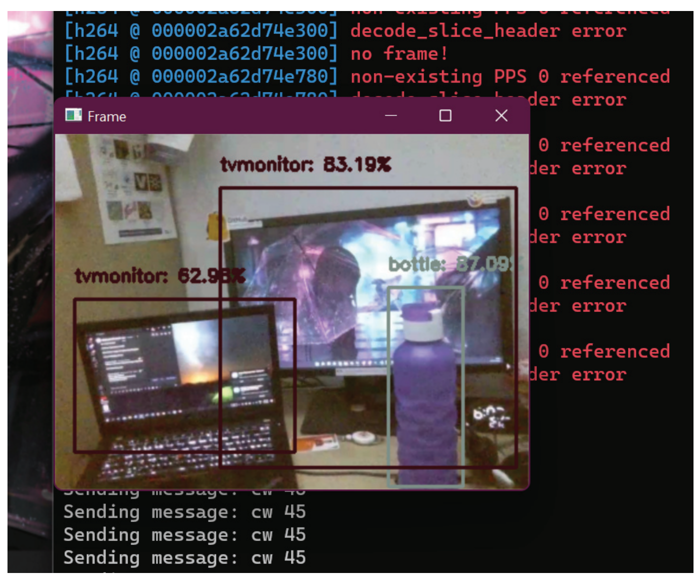


Fig. 7. Detection of multiple Object Class (TVMonitor & Bottle) by MobNetSSD Caffe model on the drone feed simultaneously

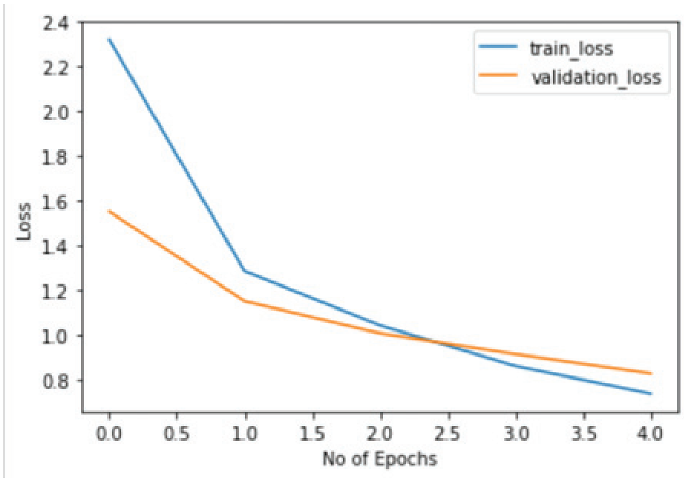


Fig. 8. Output of the model trained for 5 epochs on T4 GPU

```
[60]: single_prediction("test_images/apple_healthy.JPG")
      Original :  apple_healthy
      Apple : Healthy
[62]: single_prediction("test_images/background_without_leaves.jpg")
      Original :  background_without_leaves
      Background Without Leaves
[63]: single_prediction("test_images/blueberry_healthy.JPG")
      Original :  blueberry_healthy
      Blueberry : Healthy
[64]: single_prediction("test_images/cherry_healthy.JPG")
      Original :  cherry_healthy
      Cherry : Healthy
[65]: single_prediction("test_images/cherry_powdery_mildew.JPG")
      Original :  cherry_powdery_mildew
      Cherry : Powdery Mildew
[66]: single_prediction("test_images/corn_cercospora_leaf.JPG")
      Original :  corn_cercospora_leaf
      Corn : Cercospora Leaf Spot | Gray Leaf Spot
```

Fig. 9. Single Prediction Output of the Trained Plant Disease Detection model

Further studies and research can be done on trying to improve the UI/UX of the communication protocols between the host and the Drone. To improve the overall accuracy of the detection, better models with more layers and a more comprehensive dataset might be employed.

## Conclusion

Through this paper, we can foresee and understand that utilizing technologies for the development and cultivation of plants in a mass scale is highly beneficial. The developed models are successfully able to detect the diseases in the plants and the same model can be extended to be trained for various other species. This provides an array of benefits, wherein if the plants are tall or situated at higher places, the drone can reach them quicker and scan the area. The overall time of checking is also reduced. In large estates, the requirement of

```
================================================================
Total params: 52,595,399
Trainable params: 52,595,399
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 143.96
Params size (MB): 200.64
Estimated Total Size (MB): 345.17
----------------------------------------------------------------
```

Fig. 10. Information on the Total params formed by the layers in the model for Plant Disease detection

human labour for such inspections is reduced thus reducing the cost and expenses drastically.

Implementation of Drone Technologies in various sectors is still a new thing and just the beginning. As we progress and they become more affordable and accepted inn the society, the purpose and use cases of these models are endless. The models were solely developed flexibly for the very reason that they can be used with other models of the drone too. The developed code can be used with various models of the drones as they are Platform Independent.

There is much more left to be explored and various ways by which system can be upgraded. Utilization of complete automation along with communication via 5G will eliminate the need of WiFi connectivity and would easily let the central server communicate directly with the drone without the need of a sub-computer. As more datasets are collected and better Deep Learning Algorithms are discovered, the efficiency and the accuracy will continue to increase exponentially.

Partial source code and other information that was discussed in this project can be found in this GitHub repository. You are welcome to collaborate or modify this code in order to improvise it. Any feedback or enhancements are welcome. Please feel free to open an Issue or PR via the repository and we will gladly respond.

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