# Eagle-View: Realtime Onboard Monitoring in Agriculture for Weed Clusters

SP21 Capstone: **Final Report**

*Team Number S21-13*

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***Abstract-- In agriculture, weeds are plants that cannot be cultivated. These weeds form clusters around and steal valuable nutrition away from crops. In 2021, farmers spent on average anywhere from $4,000 to $20,000 on chemicals to rid weed infestations. By using a computer vision model that returns real-time results of weed cluster locations from the aerial images taken by a drone, we coordinate a team of drones to monitor crop fields and identify weed clusters while properly allocating each drone's limited resources such as battery life. By implementing a type of convolutional neural network model, the Feature Pyramid Network (FPN), drones process images and specifically find weed clusters in real-time. Since a drone's in-built CPU cannot process a complex computer vision model such as an FPN, a GPU is mounted on board the drones to run and process images through the model to return real-time results. Drones have limited resources, therefore the necessity of real-time results will be important in efficiently allocating these resources when monitoring large acres of farmland.***

***Keywords-- Drones, Agriculture, Real-time monitoring, Convolutional Neural Network, GPU***

## I. Introduction

The biggest costs farmers face are compromisation of crops due to weeds and chemicals used to rid weed clusters. While using bulls and other cattle to ready the soil for harvest was a common sight just a few decades ago, today, they are a rare sight and have been replaced by mechanized tractors and tools which are more efficient. Dung-based fertilizers have been replaced by highly-specialized compounds that provide the crops nutrients as well as immunity. Flooding the fields at regular intervals to irrigate the fields has been taken over by precise drip irrigation and sprinkler systems which are efficient and save time for the farmer. Even artificial selection of crops has been surpassed by genetic engineering of seeds which leads to disease-resistant, bug-resistant, and high-yield crops.

Fig. 1 An agricultural field that contains clusters of weeds as highlighted in blue circles

We can conclude that there has been a major overhauling of the agricultural industry in the past few decades leading to unprecedented yields per square mile. Comparing our technology today to many centuries ago, our agricultural methods have evolved and new tools were created to help farmers either grow or maintain crops.

However, these new high-performance methods and tools can also be fragile. One has to be aware of the precise weather and crop-health to respond timely, which is difficult as a human can only survey the fields at regular intervals in the order of days, which may not be enough to respond to problems such as a weed infestation before it can heavily destroy crops.

It also takes a lot of money and time for farmers to maintain their fields which gives them fewer opportunities to grow fresh food. In 2021, the average US farm size is 444 acres [1] and chemicals to rid weeds can cost anywhere from $10-50/acre [2], meaning farmers spend a total of $4,400-$22,200 on average. Once again, our solution proposes to have a team of  drones to survey the fields and find any recurring issues with weed infestation in the fields in real-time. The drones can quickly survey large fields and use Computer Vision (CV) algorithms to detect any weed clusters.

Implementing drones is beneficial to analyze the causes of why crops are being damaged. They can cover more area than a human and can also take images clearly from an aerial view to see more of the farmland. Our highly accurate model will then process these images and be able to exactly detect where the weed infestation is on the field early, so the farmers can take care of them before they steal valuable nutrients from the major crops causing them to be not ready for production.

Using drones for farming could pose many challenges such as drones having low battery life. If one drone loses its full battery in a short period, then another drone will need to be implemented to take turns surveying the field, thus causing the need for real-time monitoring and processing.

Our idea we proposed has similarities to the scope of other research projects being done. One similar project was done at the University of Illinois at Urbana-Champaign in a study entitled *Multi-Stream CNN for Spatial Resource Allocation: a Crop Management Application.* [3] . In this study, a MSCNN was used as an architecture to manage crops and effectively manage farm resources. In our project, we used a CNN architecture in order to detect weed clusters in real-time and use this information for drone resource allocation.

Another study was done by Purdue University and was entitled *Deep Transfer Learning for Plant Center Localization* [4]. In this study, UAVs were used to take RGB images of fields and used to localize plants. Even though the data collection methodology and scope is similar and within the realm of our research, this study did not explore the real-time aspects that could be applied to UAV monitoring of fields

Overall, our state-of-the-art is using real-time onboard processing through a GPU mounted on our drone when monitoring agricultural fields and detecting weed clusters. This real-time processing will allow for the coordination of a team of drones when monitoring fields and efficiently allocate resources among drones while dealing with issues such as battery life.

## II. Conceptual Design

We use image segmentation to predict where weed clusters are located. This method takes an image and processes it through a Convolutional Neural Network (CNN). The CNN exacts important features such as weeds and field. Then it will be reconstructed with a pixel-wise mask of those features. FPN( Feature Pyramid Network)[5] has rich semantics features at every level and builds quickly from a single input image without sacrificing representational power, speed, or memory.

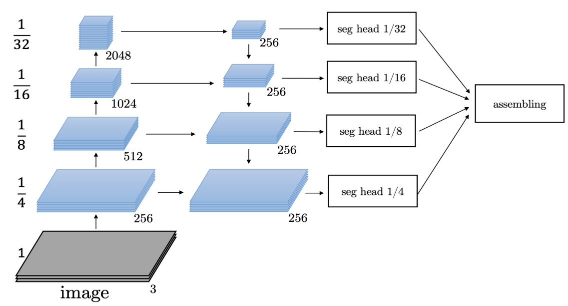


Fig.2 The FPN Model

Due to COVID-19 restrictions, we were not able to experiment with real drones to detect weed clusters in real fields. Our alternative was to emulate farm fields using software applications such as Unreal Engine and Microsoft AirSim. Unreal Engine is a software that allows for the creation of any realistic environment [6], we used this to create a realistic cornfield through a Unreal Engine package [7] and weed clusters using the Unreal Engine Open World Demo collection package that provided various foliages [8] . AirSim is a Microsoft developed package for Unreal Engine that allows a user to fly a drone in a created environment and have that drone perform realistic processes such as image collection and flight paths done through Python scripts [9].

Airim has a stock quadcopter drone which can take aerial images of our cornfield environment which are designed/created to have weed clusters through Unreal Engine. Emulating a drone was beneficial because we tested various data collection methods such as testing height and speed and recorded results from each method.

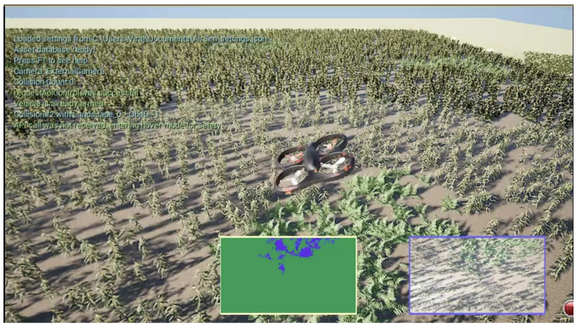

Fig.3 An AirSim drone flying in our created Unreal Engine cornfield environment. AirSim collects both segmented and scene images as shown at the bottom

For a true hardware-in-the-loop emulation, we then used images collected from the Unreal Engine emulation and sent it to a NVIDIA Jetson TX2 GPU running the computer vision algorithm [10] to process images and return real-time results.

Fig. 4 An NVIDIA Jetson TX2 was wirelessly linked to our host computer and processed AirSim images through the aforementioned computer vision model

## III. METHODS / RESULTS / APPROACH

In terms of software emulation, we began creating a cornfield environment using a cornfields package obtained from the Unreal Engine marketplace. This allows us to create an environment that's as realistic as possible compared to an actual farm, and will greatly help prove that our hardware-in-the-loop emulation results will translate well when the experiment is performed with real drones. We studied various pictures of cornfields and how crops were planted and laid out and built our environment to model a real cornfield. Using the Open World Demo Collection package, we were able to obtain various foliage that we used to emulate weed clusters, which we randomly placed in clusters throughout our field.

We then integrated Microsoft AirSim into the created environment. We wrote out a Python script specifying how the drone should fly throughout the field and also specifying what kind of pictures the drone should take using AirSim's Image APIs [11]. We then took those collected images and ran it on the model file saved in our NVIDIA Jetson TX2 and returned real-time results.

We create a dataset with the unreal images to train our model. We trained a deep neural network to detect weed clusters using image segmentation method. After we train the model we measure the two metric iou score and dice loss. IoU score stands for intersection over union which is a standard metric from object detection. It calculates how much the predicted mask overlaps with the groundtruth.

$$IoU\ Score = \frac{Area\ of\ overlap}{Area\ of\ union}$$

Another metric is the dice loss which measures the difference between grouthtruth and predicted mask. The lower the dice loss the faster the model is learning to predict correct masks. We use these metrics to measure the different models and determine the best model which fits our needs. We tested FPN, UNet, LinkNet. We choose FPN because this gives best results.

$$Dice\ Loss = 1 - \frac{2*IoU}{1+IoU}$$

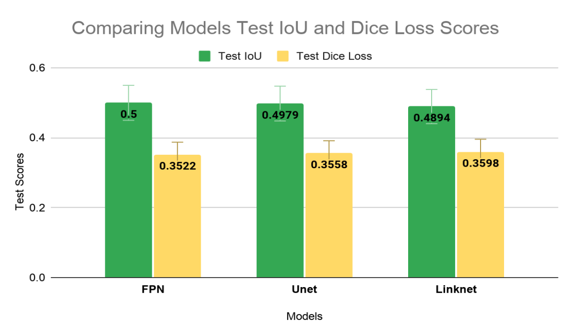


Fig.5 This is an average test IoU Score and Dice Loss results for the FPN, Unet and LinkNet models. FPN seems to have the greatest scores but all three models deliver similar results.

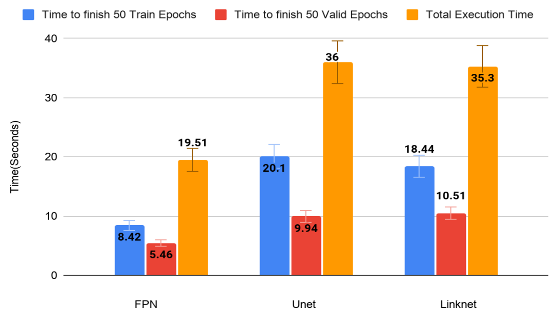


Fig. 6 Each model takes time to fully train and test a dataset. One dataset has been used to train all three models for consistency issues. Though each model delivers similar IoU and Dice Loss scores, the FPN takes much less time to fully train as opposed to Unet and LinkNet, therefore making this the superior model for our project.

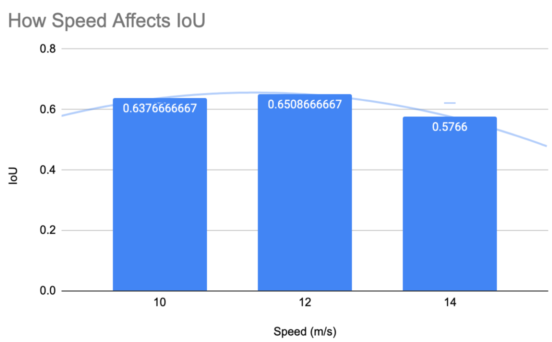


Fig. 7 This shows when trying the speed of the drone in meters per second, shows a change in IoU Score results. We recorded the drone from 10 to 14 meters/second and noticed at 12 meters/second it had the highest IoU Score of 0.65. We concluded that if a drone does not move too fast or too slow while navigating the environment, it gives more data for the model to process many visuals therefore increasing the IoU.

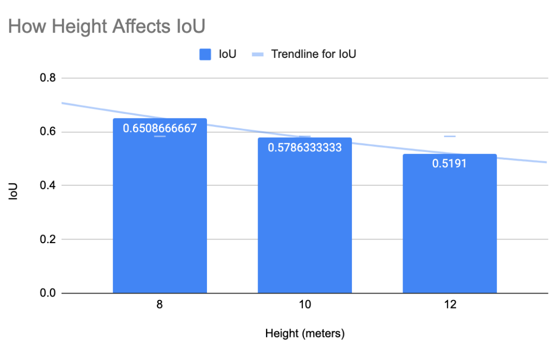


Figure 8. This shows we deployed the drone at different heights in meters and how it affects the IoU. He noticed, the closer the drone is to the drone, it has a closer view to identify objects, including weed clusters, which is the reason why lower heights would increase the IoU.

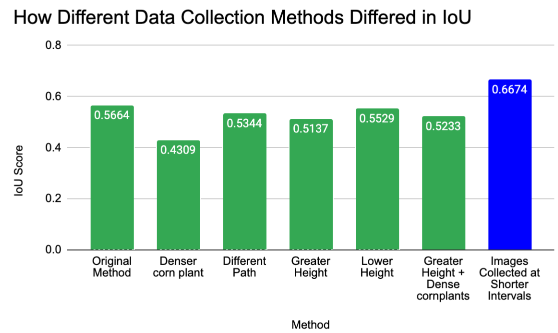


Fig.9 This shows other factors that could potentially affect the IoU score. From our observations, we noticed deploying the drone at shorter intervals delivered a huge increase in IoU Scores.

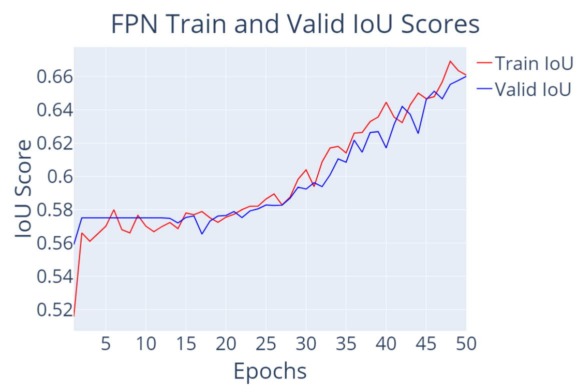


Fig.10 Here displays the Train and Valid IoU Scores when the model was trained with an image dataset. The first few epochs, the scores were low since the model needed time to teach itself what objects or shapes it can observe from the picture. Overtime, the scores increased since models began to identify different objects through training.

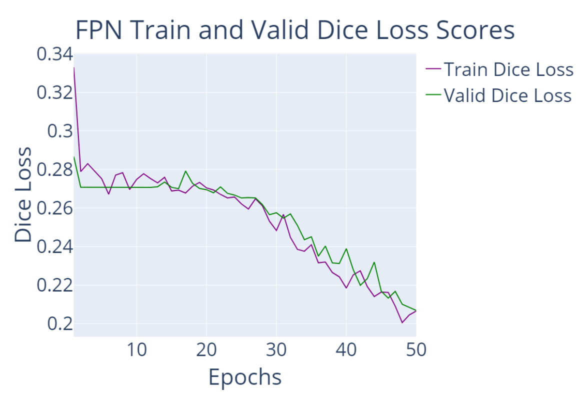


Figure 11. Here displays the Train and Valid Dice Loss Scores for when the model was also initially trained. The dice loss was a high number at first but decreased since the model overtime began familiarizing itself with the many objects or shapes it detected from the image dataset.

From our results, we were able to conclude that the best results were obtained when the drone was flying closer to the ground and at a speed of 12 meters/second. In terms of height, we chose 8 meters because this was the lowest we could allow the drone to fly without compromising the limited resources of the drone and extending the flight-time past an inefficient amount.

After collecting train and validation results, this data was then imported to the NVIDIA Jetson TX2 GPU to retrieve test results. The time to process 22 images was done in 6 seconds. The test IoU Score was 0.65 with a standard deviation of $\pm 0.032$. These results show that our images can be processed in real-time and accurately on the NVIDIA Jetson TX2.

## IV. Cost and Sustainability Analysis

We conducted this project by using many software programs to emulate a real-life setting with a drone. We used Unreal Engine but also purchased a Cornfields Package for $19.99 dollars and also bought a NVIDIA TX2 GPU for $299.99 dollars. If we were to implement this project on a large scale, then we would purchase a Parrot Bebop 2 drone or one with similar capabilities which costs about $350 dollars and still a TX2 GPU which is $300 dollars, making it a total of $650 dollars.

Since drones have a short battery life, every drone would need to be recharged over and over again, which increases electricity consumption [13]. A Parrot Bebop drone can fly for only 25 minutes and to recharge its battery, it requires 50 minutes. To operate many drones will require a great consumption of electricity. The Parrot Bebop 2 has a lithium-ion battery to function. Lithium-ion has a high energy density compared to other batteries but a concern with these batteries is overheating [14] which can restrict the drone's limitations. Despite drones having risks when deploying them, our purpose is to deploy them to accurately locate weed clusters to inform the farmer where to extract them. While there could be scenarios a drone can malfunction and possibly create environmental damage, we are helping crops thrive better without weed clusters. While we are allowed to fly a drone on fields as long as they are not endangering humans, we also have to follow the regulated drone rules such as not setting it above 400 feet or flying it 121.92 meters high. [15]

The design of this project was motivated by helping farmers save money by protecting their crops. As highlighted in our introduction, farmers spent an average total of $4,400 - 22,200 on chemicals to rid weed infestations. In addition to crops being sapped of valuable nutrition from weeds, farmers need to spend a lot of time locating and monitoring these weeds. Our product makes locating the weed fast and efficient. It saves farmers valuable time and it helps them locate weeds in real-time. Drone usage depends on the size of each field and the located weeds. Through real-time processing, we can achieve coordination of a team of drones so we can properly allocate each drone's limited resources as they are flying and capturing images through the field.

In the future, we hope to have farmers remotely control the drones flight path for it to locate weeds, but also have an automated system so that the drone flies through the field autonomously. Our product has potential to create jobs, particularly those with experience in computer vision, deep learning, and machine learning. We can expand out towards crop identification, being able to identify certain crops, animal detection for removing unwanted animals in farms and healthy soil detection.

## V. Conclusion

In conclusion, through this project, we were able to create a hardware-in-the-loop emulation of weed cluster detection in cornfields and return realtime results. We created a cornfield environment littered with weed clusters through Unreal Engine and emulated realistic drone processes such as image collection through Microsoft AirSim. We sent these collected images to a NVIDIA TX2 GPU that loaded and ran our trained computer vision and processed images through this model. Through testing, we determined the optimal data collection methodology of flying the drone at 8 meters height and 12 meters/second speed and through this, achieved on average an IoU score of 0.65 with a standard deviation of 0.032. 22 AirSim drone images were processed on the NVIDIA TX2 GPU in 6 seconds. Our emulations prove that drone images can be processed in real-time on the NVIDIA GPU. Using this, we can further conclude that when performing this experiment on a real drone, we will achieve similar results because the drone will take images similar to what we've collected from AirSim and will be running on a GPU similar to the NVIDIA TX2 GPU mounted on the drone.

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