Developing a near Real-time Weed Detection and Site-specific Drone Spray Module

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INTRODUCTION

- Conventional herbicide approaches fall short, leading to environmental concerns and herbicide resistance. A paradigm shift is crucial for precision site-specific weed management (SSWM). (Monteiro et al., 2022; Vencill et al., 2012).
- Leveraging advancements in machine vision and AI, our Real-time Weed Detection System integrates Unmanned Aerial Vehicles (UAVs) with a modular design to map weed infestations. (Menshchikov et al., 2022; Zhang et al., 2021).
- As weed-related issues rise, implementing an automated system for real-time weed detection and targeted treatment is crucial.

HYPOTHESIS

Water hemp can be detected and treated with improved efficiency using UAVs with SSWM.

OBJECTIVE

1) Develop an accurate real-time weed recognition algorithm for water hemp in cotton crops.
2) Localize individual weeds using ML algorithms for SSWM and treat them using precision spot spraying.

MATERIALS AND METHODS

Data Collection:

- Location: Texas A&M University
- Farm, TexasCrop: Cotton
- Weed species: Waterhemp (Amaranthus tuberculatus)
- Image acquisition: late summer
- Imaging platform: UAS (DJI Phantom 4 RTK)
- Sensor: RGBD Luxonix Oak-D camera
- Growth stages: Mid- to late-season escapes
- Flight modes: autonomous mode
- Flight altitude: 10 m

Project Subsystems:

Computer Vision

- Trained a neural network to identify weeds in a crop field.
- Deployed on a Jetson Nano with a live feed from a Luxonix Oak camera
- Used a GPS module to simultaneously identify and geotag weeds
  - Automates the data processing which cuts down time from 2-3 days to 2-3 hours
- Designed a 3D box to encase components (Fig 4)

Website and Database

- User Interface allowing the user to view a map of current field and add or delete coordinates
- Database stores coordinates taken from the drone and website

Spray

- Developed a pump-powered spray controlled by the microcontroller
- Developed Python script to spray whenever the drone reached the GPS coordinates pulled from the database.

MATERIALS AND METHODS

Weed localization

- The Database and Website were designed to first store coordinates captured by the computer vision system from the survey drone (Fig 11).
- MongoDB was used to store the center coordinate locations of the image frame where the weeds were detected.
- The spray drone navigated to the stored GPS coordinates (Fig 3).
- The microcontroller activated the pump based on the accurate geocoordinate locations (Fig 2 & 4).
- The spray pump turned on whenever the drone GPS was within 0.0000001 degrees from the weed coordinates.

Fig 1. Fixing the GPS base module for Validation

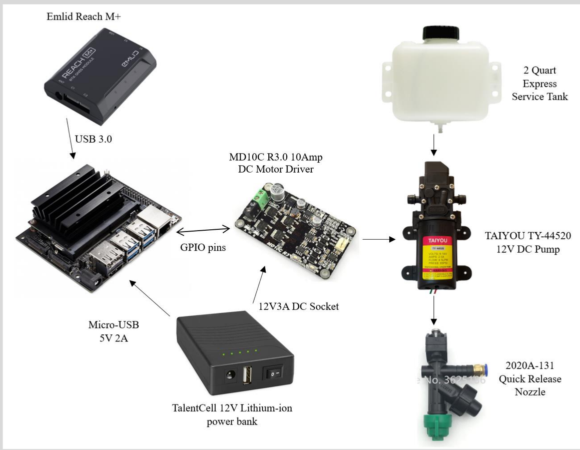

Fig 2. Internal System Components of the Spray Drone

Fig 3. The spray drone

Fig 4. 3D printed housing box

RESULTS

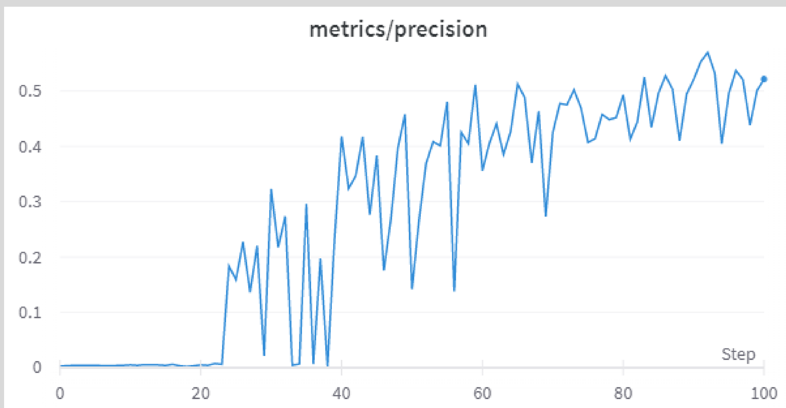

Fig 5. (YOLOv7-w6) Water hemp Precision metric

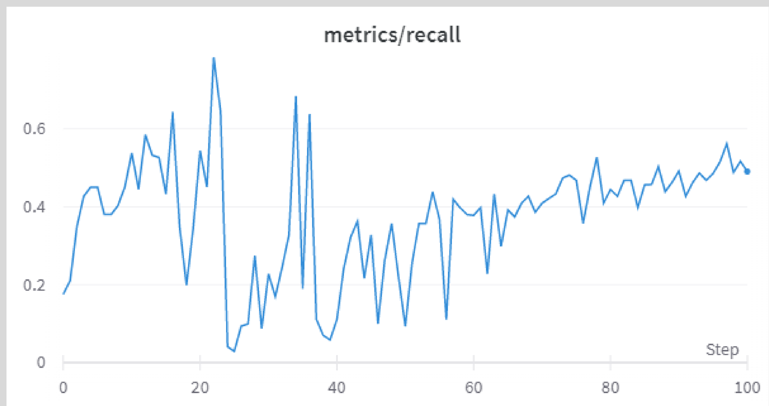

Fig 6. (YOLOv7-w6) Water hemp Recall metric

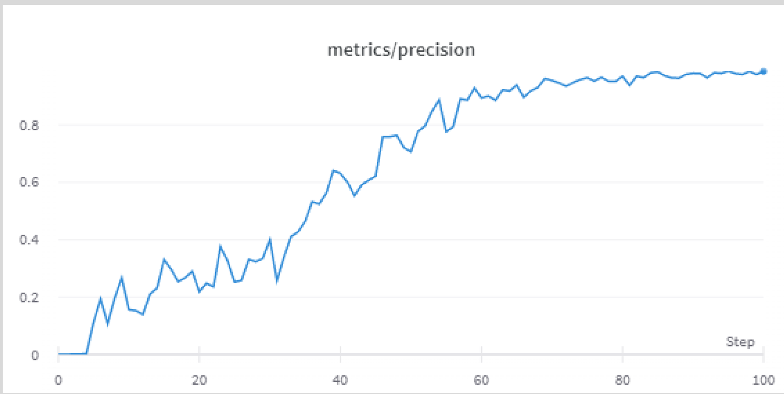

Fig 7. (YOLOv7-w6) Fake weed Precision metric

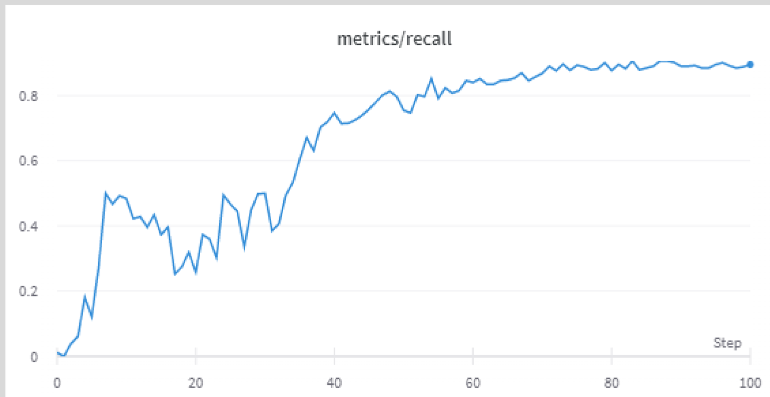

Fig 8. (YOLOv7-w6) Fake weed Recall metric

- The best-performing Water hemp model had an mAP of about 62% while the only fake weed model achieved an mAP of 95% on its first training iteration (Fig 5&7).

Fig 9. Predictions from the Water Hemp Detection Model

Fig 10. Predictions from the Fake weed Detection Model

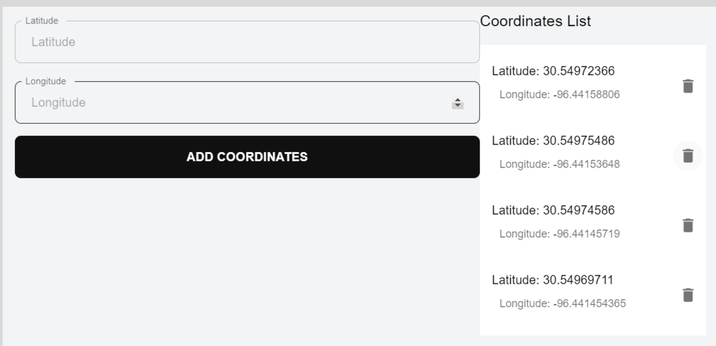

Fig 11. Website showing stored coordinates

	latitude	longitude
min	30.624215913	-96.322912465
max	30.624263859	-96.322848739
average	30.624243833	-96.322864060
range	0.000047946	0.000063726

Fig 12. GPS Variance metrics while completely still for Emlid Reach M+ GPS RTK module

RESULTS

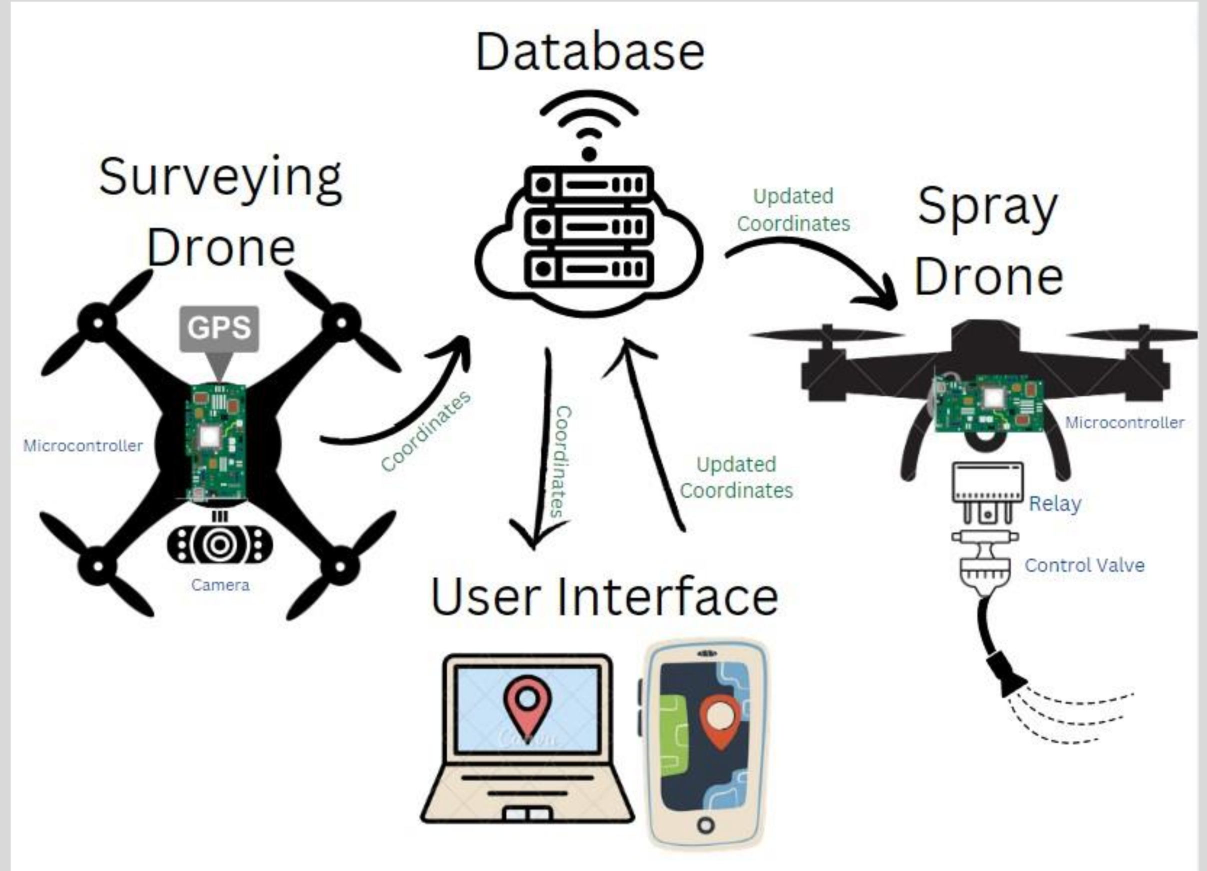

Fig 13. A schematic diagram describing the entire workflow, from aerial image collection, analysis, weed map generation, and spraying

DISCUSION AND CONCLUSIONS

- Machine learning has a high potential to detect water hemp in cotton crops using UAS imagery (Fig 9&10) (Failed to reject the hypothesis) (Zhang et al., 2021).
- At higher flight altitudes, the Pump did not have enough pressure to spray accurately.
- The GPS boasts sub-centimeter level accuracy; however, its performance depends on the weather and climate conditions (Fig 12).
- The camera had stabilization issues while in flight which reduced the water hemp detection accuracy in a dense crop cover. (Fig 9 & 13).
- Focusing on increasing the size of the training dataset and testing the model's robustness at different growth stages will improve the results in a dense crop cover.

FUTURE RESEARCH

- Testing the system at the peak of crop maturity.
- Gimbal to stabilize the camera
- Developing a boom spray system that activates based on RTK coordinates in the shapefile.

LITERATURE CITED

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TEXAS A&M AGRILIFE RESEARCH

ELECTRICAL & COMPUTER ENGINEERING

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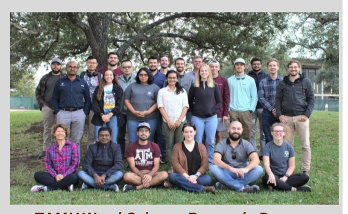

TAMU Weed Science Research Program