Project FY22-HW-006: Improving Wheat Breeding Process' Efficiency, Using AI and a Deep Scanning Model

1. What are the major goals and objectives of the research project? Objectives

(1) Implement an intelligent Deep Scanning (DS) system to capture images from an optimum close-up using photogrammetry principles to improve the Fusarium Head Blight FHB detection rates.

(2) Develop an algorithm/model using AI and DS data to enhance UAV reliability on FHB detection.

(3) Evaluate and calibrate the developed algorithm/model and improve the aerial-based phenotyping efficiency.

2. What was accomplished under these goals or objectives? *(For each major goal/objective, address these three items below.)*

a) What were the major activities?

Due to the absence of the FHB inoculated wheat (research plots) earlier in the winter 2023 and the spring of 2024, for improving the project's new features and conceptions, we conducted a trial for developing new method for object detection using a seeds dataset (seeds as objects and point of interest), to tune our model and improve our method to be used for FHB detection. The dataset consists of five different seeds including winter peas, oats, mustard seed, hairy vetch, and rape seed to simulate the capturing images using the SDSU-360 Plant Image Capturing Scanning System (SDSU-360 PICSS), designed by the Precision Ag lab team at the South Dakota State University (Plant Science Department). SDSU-360 PICSS has a 360° rotational arm with an adjustable length of 1 to 5.2 feet. A GPS were placed at one of the joints of the robot arm at the center of the 360° rotational arm. The camera was set at 3.2 feet from the GPS on the robot arm.

A stepper motor with mechanical absolute encoder was used to rotate the robot arm to any specified degree as needed (in our case, 30°). The purpose of the absolute encoder is to report a change in position and keep track of the camera position, enabling us to answer the following questions during or after rotation: What is the camera's current position? By how many degrees did the robot arm turn? In both the initial position and during rotation, the camera can observe everything within its scene range (both inside and outside the circle).

We have been working on data processing, computer programming, algorithm/models, and machine training for the collected data. In 2024 the FHB datasets the images were collected in this project at the South Dakota State University, Volga Research Farm.

We applied the same technique used for capturing the seed dataset images to the wheat images using our intelligent Deep Scanning method. We uniformly selected 237 plots and set the camera to take 52 images per 360° rotation, which equates to 1 image every second, resulting in capturing a total of 12,324 images.

We initially applied four main methods to augment the images: flipping them left to right, flipping them top to bottom, and rotating them 90 degrees or 270 degrees, thus increasing the dataset size to 49,296 images.

To be more explicit about our intentions, we will assume the change in the camera's position after a 30° counterclockwise rotation from its initial position (0°). We use a coordinate system with the X and Y offsets measured in feet. An RTK-GPS was placed at the central reference point of the SDSU-360 PICSS (the central point where the robot arm is connected to the absolute encoder). The starting position of the camera relative to the GPS will be initial camera position (0°). It is positioned along the X-axis at approximately 3.2 feet from the GPS. The next camera's new position after rotating 30 degrees counterclockwise. Based on trigonometric formulas, when rotating a point (x, y) by an angle θ around the origin, the new coordinates (x′, y′) are calculated using the following formulas:

$$\boldsymbol{x'} = \boldsymbol{x}.\mathbf{cos}(\boldsymbol{\theta}) - \boldsymbol{y}.\mathbf{sin}(\boldsymbol{\theta}), \quad \boldsymbol{y'} = \boldsymbol{x}.\mathbf{sin}(\boldsymbol{\theta}) + \boldsymbol{y}.\mathbf{cos}\,(\boldsymbol{\theta})$$

Given the camera initial offset (3.2, 2.6) and a rotation angle of 30°, the new camera offset will be expressed as:

$$\boldsymbol{x'} = 3.2 \times \cos(30°) - 2.6.\sin(30°) \cong\ 1.4712\, feet \quad (Eastward\ offset)$$
$$\boldsymbol{y'} = 3.2 \times \sin(30°) + 2.6.\cos(30°) \cong 3.8516\, feet \quad (\ Northward\ offset)$$

To convert these new offsets to the GPS coordinates of the camera, we used a Python library. Knowing the camera coordinates, once we detect objects in a scene and estimate their distance from the camera, we can accurately determine each detected object's GPS coordinates.

As various factors, such as awns obscuring background spikes, overlapping spikes, and out-of-focus spikes, can cause errors in both UAV and ground-based phenotyping data. The images for this project were collected at the South Dakota State University, Volga Research Farm. To train the computer network, we have collected 12,000 images from manually inoculated spring wheat lines (starting date did not allow us to collect the winter wheat images).

The purpose is to improve flawless data sets by capturing the images at an effective camera angle and capturing images from different views around the wheat and barley spikes.

The collected images are also used to train and calibrate an algorithm to improve the aerial-based phenotyping performance. We will use a ground-based DS system with a multispectral camera to scan the spikes, and subsequently, the collected images will be calibrated against the UAV aerial-based calibrating systems. We realized that optimizing the camera close-up and capturing images from different views around the spikes are the keys to producing higher-quality images to detect and successfully rank the stage of infection. These higher-quality images will improve the machine learning process and accuracy, enabling us to scan the points of interest beyond the color analysis. Collecting information from improved high-quality spike images results in greater machine learning capabilities and higher computational and phenotyping performance. Such strategies will improve the accuracy of FHB disease level assessment. We have also developed and fabricated a deep ground-based phenotyping cart to perform the high throughput phenotyping and detecting the FHB infected heads.

We will also work on improving the aerial-based high throughput phenotyping efficiency using scaled up deep scanning phenotyping datasets to increase selection accuracy and enhance selection efficiency during the breeding process for the FHB resistance.

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The study involved the collection of a dataset from field-inoculated plots in the Volga, South Dakota region. Subsequently, the dataset was subjected to thorough cleaning and annotation procedures. A novel 360-degree phenotyping method was conceptualized and developed for comprehensive plant assessment. SDSU - 360 Plant Image Capturing System (SDSU-360 PICS) was designed by the Precision Ag lab team at Plant Science Department and constructed at the fabrication shop of South Dakota State University. The experiment was subsequently conducted at the SDSU Volga Inoculated Research Farm. The primary focus of this experiment was to assess the foundational principle of the concept, with wheat FHB disease serving as the primary point of interest for evaluation. The study's findings demonstrate the advantages of employing the 360-degree method for accurate and reliable disease detection purposes. The effectiveness of this phenotyping approach for disease detection was evaluated using Deep Learning techniques.

Despite the extensive and intricate nature of the data collected, it required specific fine-tuning to suit our objective of identifying Fusarium Head Blight (FHB) disease. We meticulously selected and labeled 500 images, each segmented into three distinct categories: the background, disease-infected area, and healthy plant section. We accomplished this task via the PixAnotator software.

We also created and applied a convolutional neural network (CNN) model with an approach of starting with a strong yet uncomplicated model to establish our benchmark. The U-Net model was an excellent fit for this purpose. The architecture of U-Net is symmetric and has a U-shaped design, hence the name. The uniqueness of this model lies in its expansive path, which allows location information to be propagated to higher-resolution layers. This feature makes it incredibly effective for tasks that require fine-grained segmentation, including our use case of detecting the FHB disease. Implementing U-Net for our dataset provided us with an excellent starting point for our analysis. The model was trained and tested on the dataset we had previously collected and annotated. The first set of results emerged as the model sifted through the dataset, learning to discern the subtle differences between the disease area, healthy plant area, and background. Our simple U-Net model achieved an F-score of 0.869, a sensitivity of 0.910, a specificity of 0.907, and an accuracy of 0.912.

Meanwhile, the Jaccard Similarity Index - a crucial metric in image segmentation tasks - stood at 0.912. These results were promising, yet there was room for improvement. The following steps would involve innovating this base model to enhance its performance.

In the context of FHB detection, an intellectual property patent, two scientific research papers, and two posters have been published. Among these publications, one manuscript elaborates on the advantages of 360-degree Plant Phenotyping for disease detection. These works were presented at the ASABE Conference in Omaha in July 2023. The second paper, focusing on early disease detection, is currently pending publication.

b) What were the significant results?

We used YOLOv9 model generalized efficient layer aggregation network (GEL AN) to train our dataset which was divided into three sets: train, validation and test set. The model did well across all classes, with an overall precision (P) of 0.919 and recall (R) of 0.906. The mean Average Precision (mAP) for IoU threshold 0.50 (mAP50) is 0.916, and for the range of IoU thresholds 0.50 to 0.95 (mAP50-95), it is 0.548 (Table 1)

Table 1 Training results summary

Class	Instances	P	R	mAP50	mAP50-95
all	41793	0.919	0.906	0.916	0.548
1	7320	0.877	0.855	0.86	0.456
2	11234	0.901	0.867	0.899	0.488
3	8889	0.977	0.966	0.979	0.700
4	7484	0.898	0.929	0.949	0.573
5	6866	0.898	0.915	0.895	0.524

The evaluation of different seed classes based on precision (P), recall (R), mean Average Precision at 50% IoU (mAP50), and mean Average Precision averaged over IoU thresholds from 50% to 95% (mAP50-95) indicates that class 3 achieved the highest precision at 0.977 and the highest mAP50 at 0.979, demonstrating superior detection accuracy and reliability. Class 2 seed follows with a precision of 0.901 and an mAP50 of 0.899, indicating high accuracy but with lower consistency across different IoU thresholds as reflected by its mAP50-95 of 0.488. Class 4 seed also performed well with a precision of 0.898, the highest recall at 0.929, and an mAP50 of 0.949, showcasing a strong balance between precision and recall.

Class 5 with a precision of 0.898 and an mAP50 of 0.895, showed good detection performance but slightly lower than Class 4 seeds. Lastly, Class 1 had the lowest precision at 0.877 and the lowest mAP50 at 0.86, indicating more false positives and the most variability in detection performance as indicated by its mAP50-95 of 0.456.

The model and evaluation results on the dataset clearly show that the size, color, and the close-up angle of the camera at which the images were taken impact the quality of the images during training and evaluation. The test trial of our deep learning model in real time was conducted using a stereo vision camera called Intel RealSense d435i. The RealSense camera is equipped with one depth camera, two infrared cameras and one-color camera.

After completing the test trial, we will analyze our results, make further assessments, and determine how we can extend improve the FHB dataset and detection. The previous images taken for the seeds dataset and the initial test results provided us with insights on how to adjust our robot system and camera parameters to capture high-quality images for our FHB detection dataset. We plan to use at least one of the principles of photogrammetry.

Photogrammetry is defined as a technique used to obtain accurate three-dimensional (3D) information, measurements, and spatial data from two-dimensional (2D) photographs. The process involves analyzing images to extract geometric and spatial data, enabling the creation of detailed models, maps, and reconstructions. This technique leverages the principles of perspective geometry, where multiple overlapping photographs taken from different angles are used to triangulate the position of points in 3D space. By identifying corresponding points in two or more images, precise measurements and 3D models can be constructed.

In our project, we will use aerial photography, which is one of the principles of photogrammetry. There are three types of vertical, low oblique, and high oblique aerial photography. The camera axis was highly tilted (around 60 degrees), covering a larger area with a visible horizon and significant relief. Using our intelligent Deep Scanning (DS) robot system, images will be captured from an optimal close-up angle. The picture below demonstrates different camera angles that might be used for capturing the necessary images for photogrammetric analysis.

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c) List key outcomes or other achievements.

The provided images and precision scores suggest several areas for further model improvement.

- **Consistency Across Categories:** While the model performs well for oats and winter peas, the variability in precision scores for mustard seed, rape seed, and hairy vetch suggests the need for additional training data or enhanced algorithms to improve consistency.

- **Angle and Lighting Conditions:** The annotations demonstrate that the model's performance may vary with different angles and lighting conditions. Ensuring uniform image capture conditions and augmenting the dataset with diverse angles and lighting could enhance model robustness.

- **Specific Challenges with Certain Seeds:** The lower and more variable precision scores for rape seed and hairy vetch indicate that these categories present specific challenges. Further analysis to understand these challenges and targeted improvements in the model could enhance detection accuracy.

The analysis of the annotated images highlights the overall effectiveness of the intelligent Deep Scanning (DS) system while identifying areas for improvement. The high precision scores on the tests demonstrate the model's potential, while the variability for other categories points to opportunities for further refinement. By addressing these challenges, we can enhance the system's reliability and accuracy in detecting and classifying the FHB rating.

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3. **What opportunities for training and professional development has the project provided?**
For professional development we are working on an article "FHB detection with deep learning architectures and advanced image processing techniques." This will improve knowledge about transformations and their applications in image analysis.

4. **How have the results been disseminated to communities of interest?**
One poster and presentation published at the Cincinnati, OH National FHB Forum (Optimum Closeup in Wheat FHB Detection with 360-Degree Deep Scanning Method and Using an Efficient Transformer Model). Three posters and presentation published at the Tampa National FHB Forum. Two papers published with acknowledgment of federal support in 2023 ASABE Annual International Meeting, (American Society of Agricultural and Biological Engineers).

5. **What do you plan to do during the next reporting period to accomplish the goals and objectives?**
There are different models from what we used (standard UNet model for segmentation) before that we my use in the next reporting including, ResNet50 + PSPNet, MobileNetV3 + DeepLabV3+, W48-HRNet, ResNet50 + UNet++, and ResNet50 + Pyramid Attention Network (PAN). Also, we will use advanced architectures (incorporate more sophisticated architectural designs like pyramid pooling, multi-scale context aggregation, and attention mechanisms, enhancing their ability to capture fine details and contextual information