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

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

Fusarium Head Blight (FHB), or scab, is a devastating disease in wheat and barley, caused by *Fusarium graminearum*. It causes kernel bleaching, reduced yield, and the production of toxic mycotoxins. Early rating/ranking of the resistivity and receptivity of the newly developed lines. This project leverages advanced imaging, deep learning, and photogrammetry to provide a robust, objective, and high-throughput solution for real-time FHB detection methods that are efficient and not subjective.

(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.)*

Increasing phenotyping accuracy in wheat breeding by developing a scalable and real-time FHB detection system using multi-angle imaging and machine learning.

- 12,324 wheat spike images from 237 plots the SDSU-360 Plant Image Capturing System (PICSS) with 360° coverage and augmented the dataset to 49,296 images.

Dataset overview

Out of 12,324 total images, 950 were annotated and used as the base dataset. This dataset was augmented using Roboflow's internal augmentation methodologies.

- **Augmentation process**
  Resizing: All images were resized to 512x512 pixels (the initial median image ratio was 6720x4480)
  Shearing: A shear transformation of 1 degree horizontally and 1 degree vertically was applied to the images.
  Classes: The dataset includes two categories: healthy and unhealthy wheat spikes affected by FHB. However, not all spikes are annotated due to image quality or occlusions.
  Imbalance: There was a significant imbalance in the dataset, with more unhealthy wheat spikes annotated compared to healthy ones.
- Developed 3D-printed mounts, stabilized camera holders, and configured static IPs for 16 Raspberry Pi camera modules.
- Created a centralized web server with GUI for live camera preview and remote triggering of all modules.

- A dual-frame camera system was developed using 16 Raspberry Pi V2 cameras on a 360° rotatable cart, capturing both vertical and horizontal perspectives.
- Integrated centralized control using a lightweight Python HTTP server to synchronize and manage image acquisition.
- Applied deep learning (U-Net, YOLOv9, CNN) for segmentation, detection, and classification of diseased wheat spikes.
- Trained on annotated datasets collected at the SDSU Volga Research Farm from field-inoculated plots.

What were the significant results?

- Achieved seamless 360° image acquisition with accurate spatial tracking of camera.
- Enabled reliable synchronized image and metadata collection (camera position, angles).
- Ensured repeatable, angle-consistent imaging for model training and field calibration.

Key Outcomes:

- Robust DS system for high-resolution multi-view imaging.
- Custom photogrammetry integration enabling object localization.
- Reproducible platform adaptable to other crops and diseases.

What were the major activities?

- Annotated 500+ images into background, healthy, and unhealthy spikelets using PixAnotator.
- Trained segmentation model (U-Net) and object detection models YOLOv9 Generalized Efficient Layer Aggregation Network (GELAN) on seed and wheat spike datasets.
- YOLOv9 model evaluated on multiple seed classes; prepared for wheat spike detection.

What were the significant results?

- Enhanced FHB detection and severity ranking with real-world deployment feasibility.
- Demonstrated improved accuracy of spikelet-level detection using side-view imaging.
- Identified the importance of optimal angle and consistent illumination for reliable disease classification.
- Built pipelines for integrating image metadata with prediction for precise spatial mapping.

Challenges: While the models successfully segmented wheat spikes, issues such as image quality, including blurriness and low contrast, impacted the segmentation performance. Despite these challenges, the model showed gradual improvements over the epochs. The model's performance was measured using metrics such as Intersection over Union (IoU), Precision, Recall, and the F1 Score. These metrics are important for understanding how well the model segmented the wheat spikes and correctly classified them as healthy or unhealthy.

U-Net results on wheat spike segmentation

- F-score: 0.869
- Sensitivity: 0.910
- Specificity: 0.907
- Accuracy: 0.912
- Jaccard Index: 0.912

YOLOv9 (GELAN) performance

- Precision (P): 0.919
- Recall (R): 0.906
- mAP@0.5: 0.916
- mAP@0.5–0.95: 0.548

Key outcomes or other achievements

1. Designed and deployed a **dual-frame multi-angle camera system**.
2. Achieved **centralized synchronization** of 16 Raspberry Pi cameras with real-time preview.
3. Developed deep learning pipelines (U-Net, YOLOv9) with high detection accuracy.
4. Presented and published research (from the beginning of this project):
    - 1 intellectual property patented, 1 intellectual property under patent review
    - 2 peer-reviewed papers (2 pending publication)
    - 5 posters and conference presentations (FHB Forum and ASABE Annual Meeting).
5. Achieved modular system design, extensible to other crop phenotyping applications.

3. What opportunities for training and professional development has the project provided?

- Raspberry Pi configuration and networking
- Computer vision, image annotation, model training
- Photogrammetry, 3D mounting design, and robotic data acquisition
- Deep learning frameworks (YOLO, U-Net, segmentation networks)

4. How have the results been disseminated to communities of interest?

- Two papers acknowledged federal support (ASABE conference proceedings).
- Two manuscripts in preparation focused on early-stage disease detection and two paper detailing advantage of 360° phenotyping method will be submitted.

5. What do you plan to do during the next reporting period to accomplish the goals and objectives?

To further improve the resistance screening methods and FHB scoring, and make them more efficient, accurate and easy to use and more reliable for large-scale breeding programs, we work to make the screening technology automated, to complement and enhance existing screening technologies by providing higher resolution while dynamically adjusting to plant height variations within a breeding plot. The goal is to provide precise, rapid, and objective ratings of FHB resistance across breeding plots.

Planned activities (next reporting period):

- Collect more images from FHB inoculated nursery at the SDSU research field (Volga) with the new system, and complete annotation of collected wheat images.
- Train models: U-Net++, DeepLabV3+, MA-Net, PAN, Attention U-Net, and updated YOLOs.
- Develop real-time severity prediction and spikelet counting models.
- Integrate predictions with metadata for disease heatmaps.
- Validate model predictions with breeder ratings across diverse plots.
- Prepare high-impact publications on DS platforms, data, and model performance.
- Develop training guides for breeders and phenotyping teams.

Projected timeline and timeframe activities:

Q3 2025: Complete data collection, annotation, and improve training severity models

- Collect more images from the FHB-inoculated nursery at the SDSU research field (Volga) using the new imaging system.
- Complete annotation of collected wheat images (e.g., labeling spikelets, FHB symptoms, etc.).
- Enhance model training for severity detection and segmentation tasks: U-Net++, DeepLabV3+, MA-Net, PAN, Attention U-Net, and updated YOLO variants

Q4 2025: Integrate metadata, build disease mapping pipeline

- Develop real-time severity prediction and spikelet counting models.
- Integrate prediction outputs with collected metadata.
- Develop and implement a pipeline for disease severity heatmap generation across plots using integrated data.

Q1 2026: Validate model accuracy in field trials

- Validate trained model predictions (e.g., severity scores, spikelet counts) against breeder ratings collected from diverse field plots.
- Assess the consistency, accuracy, and generalizability of the models under real-world conditions.

Q2 2026: Finalize and publish manuscripts, release training materials

- Prepare and submit high-impact publications focused on:
    - Digital phenotyping platforms
    - Collected datasets and annotation methodology
    - Comparative performance of segmentation and detection models
- Develop and disseminate training guides for breeders and phenotyping teams to support adoption of the tools in breeding programs.