USDA-ARS | U.S. Wheat and Barley Scab Initiative

FY22 Performance Progress Report

Due date: July 26, 2023

Cover Page

USDA-ARS Agreement ID:	59-0206-2-143
USDA-ARS Agreement Title:	Improving Phenotyping Accuracy Using Artificially Intelligent Technologies and Innovative Method
Principle Investigator (PI):	Ali M Nafchi
Institution:	South Dakota State University
Institution UEI:	DNZNC466DGR7
Fiscal Year:	2022
FY22 USDA-ARS Award Amount:	$28,101
PI Mailing Address:	Raven Precision Ag Center, 209 140 Raven Box 2100A Brookings, SD 57007
PI E-mail:	ali.nafchi@sdstate.edu
PI Phone:	605-688-4774
Period of Performance:	May 1, 2022 – April 30, 2026
Reporting Period End Date:	April 30, 2023

USWBSI Individual Project(s)

USWBSI Research Category[*]	**Project Title**	**ARS Award Amount**
HWW-CP	Improving Wheat Breeding Process' Efficiency, Using AI and a Deep Scanning Model	$28,101
FY22 Total ARS Award Amount		$28,101

I am submitting this report as an: ☒ Annual Report

I certify to the best of my knowledge and belief that this report is correct and complete for performance of activities for the purposes set forth in the award documents.

Principal Investigator Signature

7-26-2023
Date Report Submitted

[*] BAR-CP – Barley Coordinated Project
DUR-CP – Durum Coordinated Project
EC-HQ – Executive Committee-Headquarters
FST-R – Food Safety & Toxicology (Research)
FST-S – Food Safety & Toxicology (Service)
GDER – Gene Discovery & Engineering Resistance
HWW-CP – Hard Winter Wheat Coordinated Project
MGMT – FHB Management
MGMT-IM – FHB Management – Integrated Management Coordinated Project
PBG – Pathogen Biology & Genetics
TSCI – Transformational Science
VDHR – Variety Development & Uniform Nurseries
NWW –Northern Soft Winter Wheat Region
SPR – Spring Wheat Region
SWW – Southern Soft Red Winter Wheat Region

Project 1: 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 to improve the 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?

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. The study involved the collection of a dataset from field-inoculated plots 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 was 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 were also used to train and calibrate an algorithm to improve the aerial-based phenotyping performance. We have also developed and fabricated a deep ground-based phenotyping cart to perform the high throughput phenotyping and detection of the FHB-infected heads. We used this ground-based deep scanning system with an RGB camera to scan the spikes and, subsequently, the collected images to 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. On the data processing side, we have been working on computer programming, algorithm/models, and machine training for the collected data. 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. 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.

b) What were the significant results?

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.

c) List key outcomes or other achievements.

In the context of FHB detection, an intellectual property patent (with acknowledgment of federal support), two scientific research papers, and two posters have been published.

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

One graduate student is working on this project. The other will start on Spring 24. Three posters and presentations at the 2022 National FHB Forum and two presentations with acknowledgment of federal support in the 2023 ASABE Annual International Meeting (American Society of Agricultural and Biological Engineers).

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

Three posters and presentations with acknowledgment of federal support were published at the 2022 National FHB Forum. Also, two papers were published with acknowledgment of federal support in the 2023 ASABE Annual International Meeting (American Society of Agricultural and Biological Engineers).

Publications, Conference Papers, and Presentations

Please include a listing of all your publications/presentations about your FHB work that were a result of funding from your FY22 grant award. Only citations for publications published (submitted or accepted) or presentations presented during the **award period** should be included.

Did you publish/submit or present anything during this award period May 1, 2022 – April 30, 2023?

☒ Yes, I've included the citation reference in listing(s) below.

☐ No, I have nothing to report.

Journal publications as a result of FY22 award

List peer-reviewed articles or papers appearing in scientific, technical, or professional journals. Include any peer-reviewed publication in the periodically published proceedings of a scientific society, a conference, or the like.

Identify for each publication: Author(s); title; journal; volume: year; page numbers; status of publication (published [include DOI#]; accepted, awaiting publication; submitted, under review; other); acknowledgement of federal support (yes/no).

Books or other non-periodical, one-time publications as a result of FY22 award

Report any book, monograph, dissertation, abstract, or the like published as or in a separate publication, rather than a periodical or series. Include any significant publication in the proceedings of a one-time conference or in the report of a one-time study, commission, or the like.

Identify for each one-time publication: Author(s); title; editor; title of collection, if applicable; bibliographic information; year; type of publication (book, thesis, or dissertation, other); status of publication (published; accepted, awaiting publication; submitted, under review; other); acknowledgement of federal support (yes/no).

Other publications, conference papers and presentations as a result of FY22 award

Identify any other publications, conference papers and/or presentations not reported above. Specify the status of the publication.

Ahmed Abdalla, Babak Azad, Karl Glover, Sunish Kumar Sehgal, Shaukat Ali, Kwanghee Won and Ali Mirzakhani Nafchi. (2022). FHB Stage Detection, Deep Scanning Robot. Proceedings of the 2022 National Fusarium Head Blight Forum; Tampa, FL. December 4-6, 2022. Retrieved from: https://scabusa.org/forum/2022/2022NFHBForumProceedings.pdf. Acknowledgment of federal support: yes.

Babak Azad, Ahmed Abdalla, Karl Glover, Sunish Kumar Sehgal, Shaukat Ali, Kwanghee Won and Ali Mirzakhani Nafchi. (2022). Large-scale Wheat-FHB Disease Analysis with Deep Neural Networks. Proceedings of the 2022 National Fusarium Head Blight Forum; Tampa, FL. December 4-6, 2022. Retrieved from: https://scabusa.org/forum/2022/2022NFHBForumProceedings.pdf. Acknowledgment of federal support: yes.

Ali Mirzakhani Nafchi, Ahmed Abdalla, Babak Azad, Karl Glover, Sunish Kumar Sehgal, Shaukat Ali and Kwanghee Won. (2022). Improving Wheat Breeding Process Efficiency, Utilizing AI and Deep Scanning Model. Proceedings of the 2022 National Fusarium Head Blight Forum; Tampa, FL. December 4-6, 2022. Retrieved from: https://scabusa.org/forum/2022/2022NFHBForumProceedings.pdf. Acknowledgment of federal support: yes.

Improving FHB Screening in Wheat Breeding Using an Efficient Transformer Model
In 2023 ASABE Annual International Meeting (p. 1). American Society of Agricultural and Biological Engineers. (doi:10.13031/aim.202300569). Acknowledgment of federal support: yes.

Maintaining Optimum Closeup in Wheat FHB Detection Using 360-Degree Deep Scanning Method
In 2023 ASABE Annual International Meeting (p. 1). American Society of Agricultural and Biological Engineers. (doi:10.13031/aim.202300615). Acknowledgment of federal support: yes.