Intelligent Pest Identification for Precision Agriculture using Deep Learning

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Anika Bhat is a 12th grade student at Moreau Catholic High School in Hayward, CA, USA. She is currently an Oakland Space Academy Intern at the Chabot Space & Science Center (Oakland, CA, USA), where she previously worked as a volunteer, peer mentor, and student researcher for 3 years. For her undergraduate studies, she plans to pursue engineering with a multidisciplinary approach involving aerospace, electronics, computer science, and AI.

Her research experience/projects include the following:

- *Extending the Astrobee Free-Flying Robot Dataset* (2025) – NASA Ames Research Center Internship
- *AIRA: A New Era of Augmented Reality* (2025) – Harvard Crimson Business Competition
- *Vision-Based Approach & Landing for Advanced Air Mobility Autonomous Aviation* (2024) – NASA Ames Research Center Internship
- *Allergen Alert: Food and Cosmetic Safety* (2024) – allergen detection alert system & mobile app
- *A Deep Learning Model to Predict Whether a Breast Tumor is Malignant or Benign* (2023)
- *MEDeBuddy: A simple & portable electronic health tracker to manage health for asthmatic patients* (2021)
- *Trash to Treasure: Generation of electricity from household waste using Microbial Fuel Cells* (2020)

Introduction

- Global Food Security & Wheat:
  - Second most produced grain in the world: 785 tons in 2023-24 [1]
  - Pests destroy ~157 million tons of grain/yr, causing food insecurity [1, 2]
- Economic & Agricultural Crisis:
  - **20%–40% of global crop loss/yr due to pests: $70 billion loss/yr** [3]
- Common Wheat Pests:
  - Aphids, Green Bug, Ceredonta Denticonis, Spider Mite, Penthaleus Major, Wheat Blossom Midge, Wheat Sawfly
- Current Methods of Pest Monitoring & Limitations:
  - Farmers rely on reactive & delayed pest detection, leading to irreversible crop damage & overuse of pesticides.
  - Pest Monitoring Challenges: Variable life cycle, nighttime activity, need for precise timing to catch peak activity
  - Broad-spectrum pesticide overuse increases pest resistance.
- **AI-powered agricultural image analysis is crucial in modern agriculture [4]**
- **Opportunities for AI-driven image analysis in wheat pest control:**
  - Continuous monitoring & early detection of pests to prevent yield loss
  - Rapid, scalable & precise pest identification

Research Objective

To develop a deep learning model & a web application to provide real-time pest identification and targeted pest-removal suggestions to mitigate crop loss

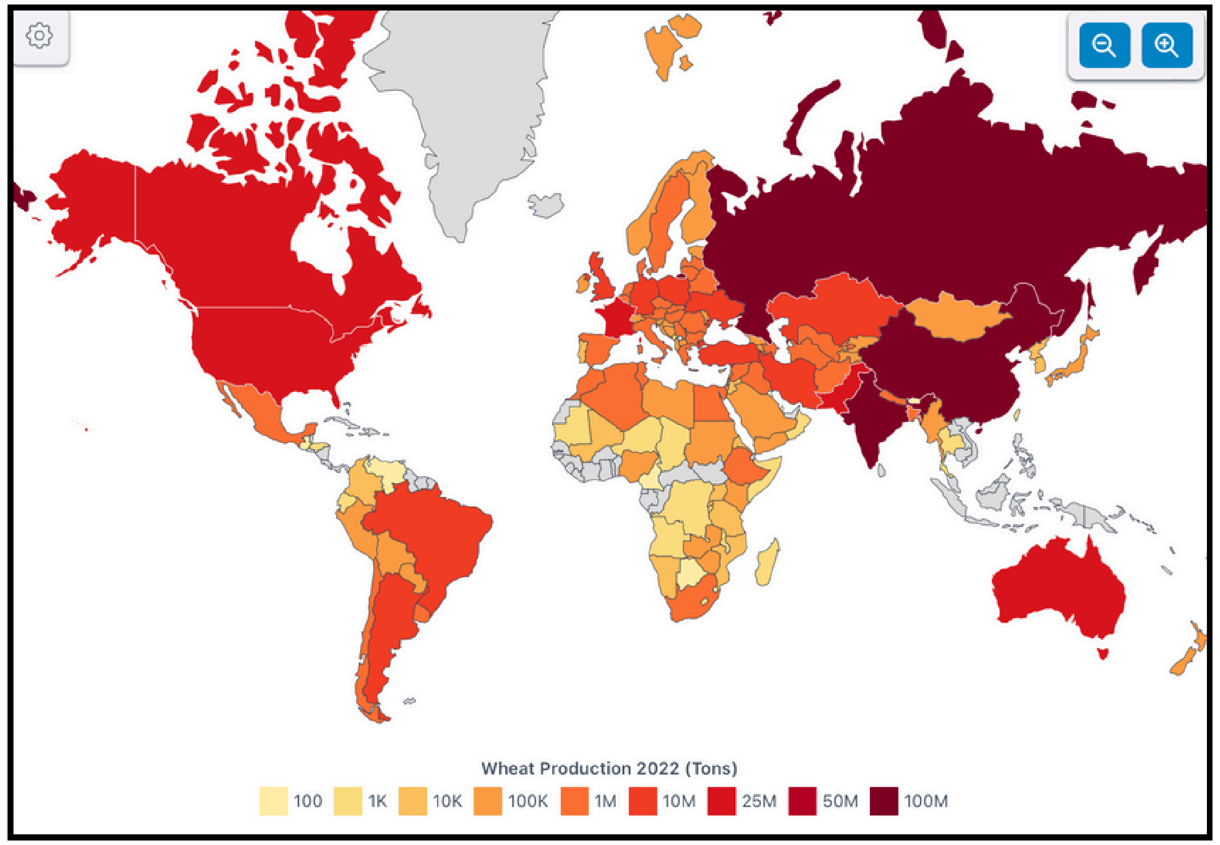

Figure 1. Wheat production by country in 2022 [1]

Figure 2. Green bug (type of wheat pest)*

*Chapter 22: Insect Pests of Wheat - SDSU Extension, extension.sdstate.edu/sites/default/files/2020-03/S-0005-22-Wheat.pdf.

Methodology

Dataset:

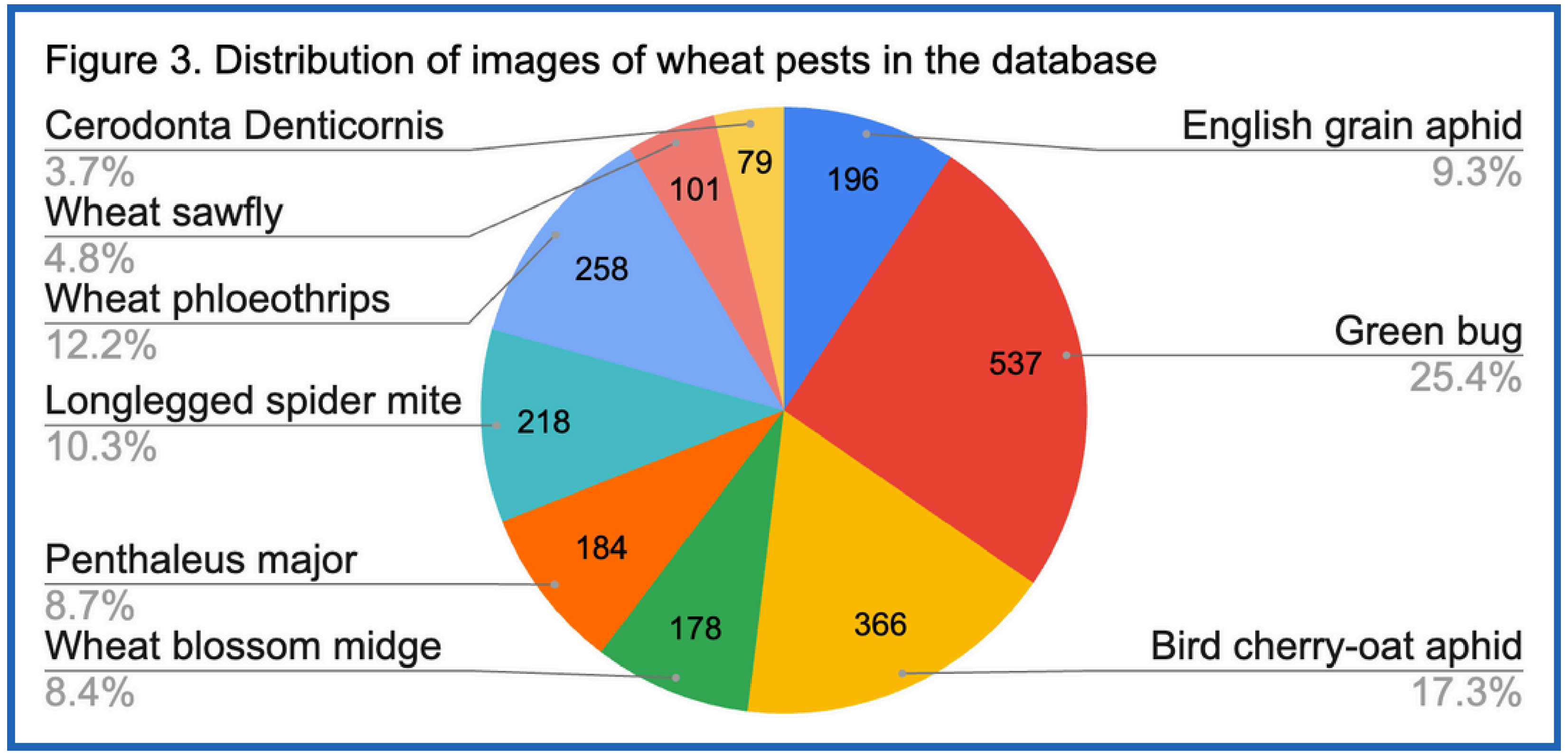

Figure 3. Distribution of images of different categories of wheat pests

- A publicly available database of pests [16] was downloaded, and only the images of wheat crop pests (9 categories) were extracted. The dataset of wheat crop pests was split into training, testing, and validation sets.

Methodology (cont.)

Machine Learning:

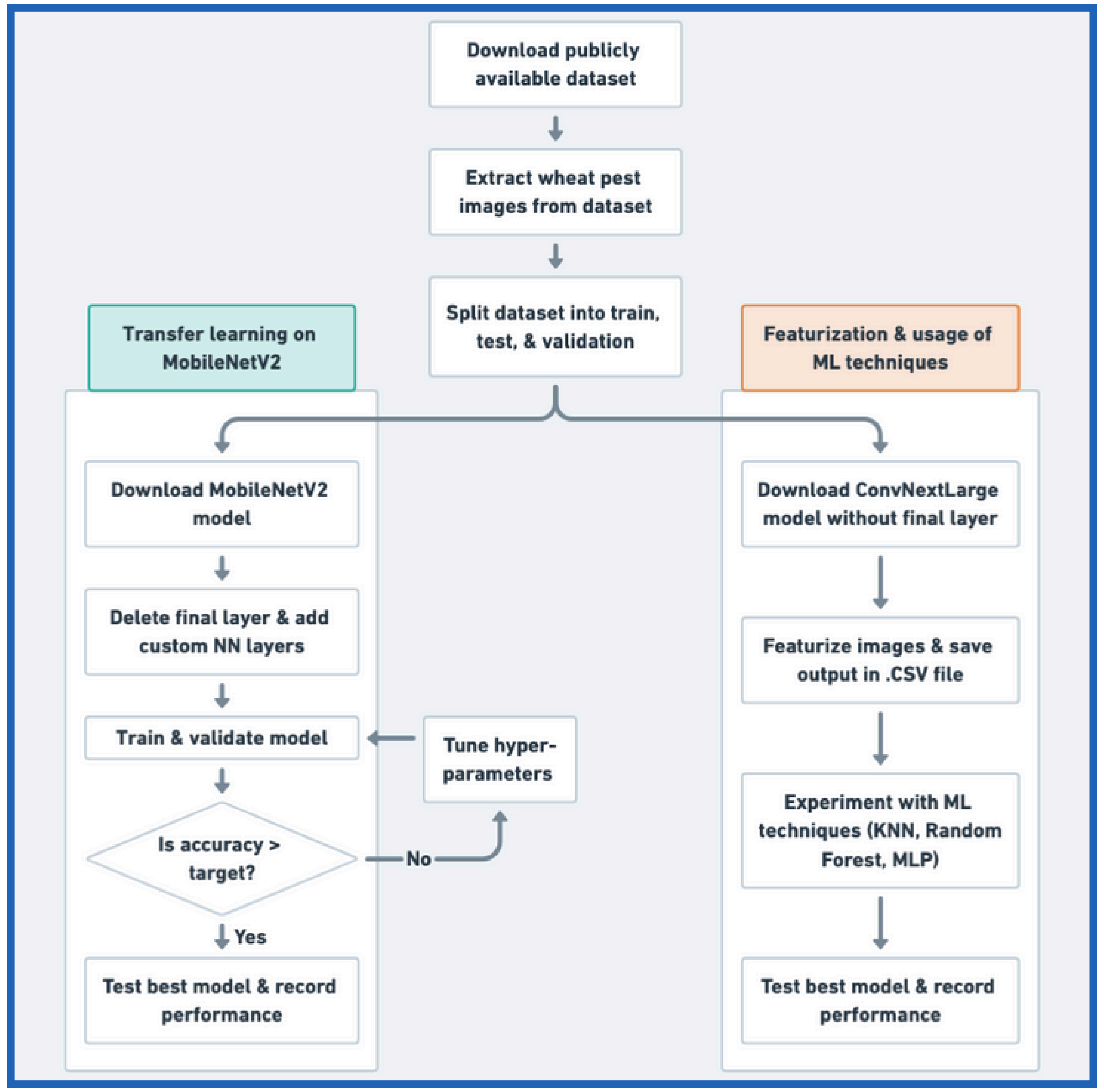

Figure 4. Machine Learning pipeline: steps followed for building ML models.

- Approach 1: Transfer Learning on *MobileNetV2*
- Approach 2: Featurization & ML Techniques

Device:

Figure 5. Hardware architecture diagram.

- power supply: solar-powered power bank
- microcontroller board: Seeed Studio XIAO ESP32S3 Sense
  - WiFi-enabled
    - built-in camera connected to microcontroller via Camera Serial Interface (CSI)

Methodology (cont.)

Device (cont.):

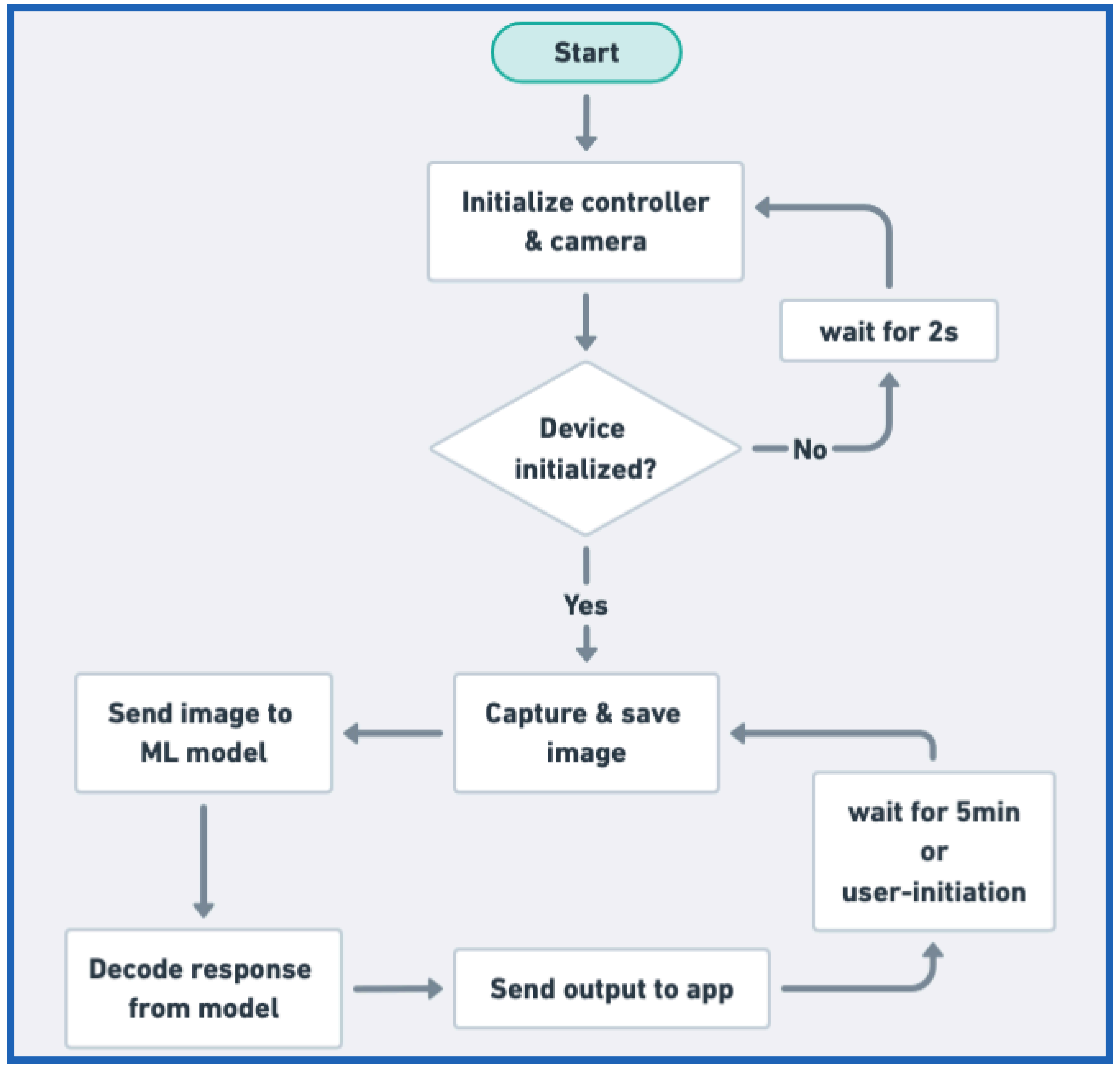

Figure 6. Firmware flowchart: logic implemented in the device.

Web Application:

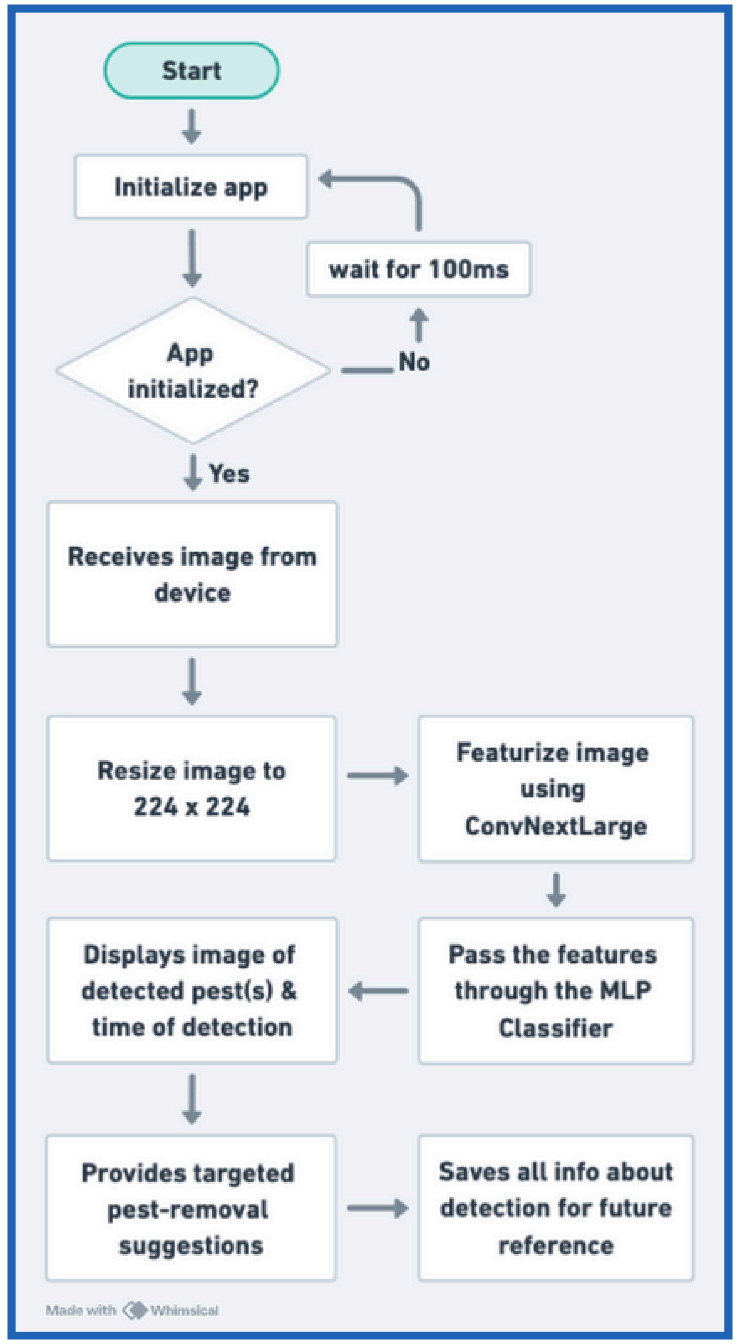

Figure 7. Application flowchart.

Results

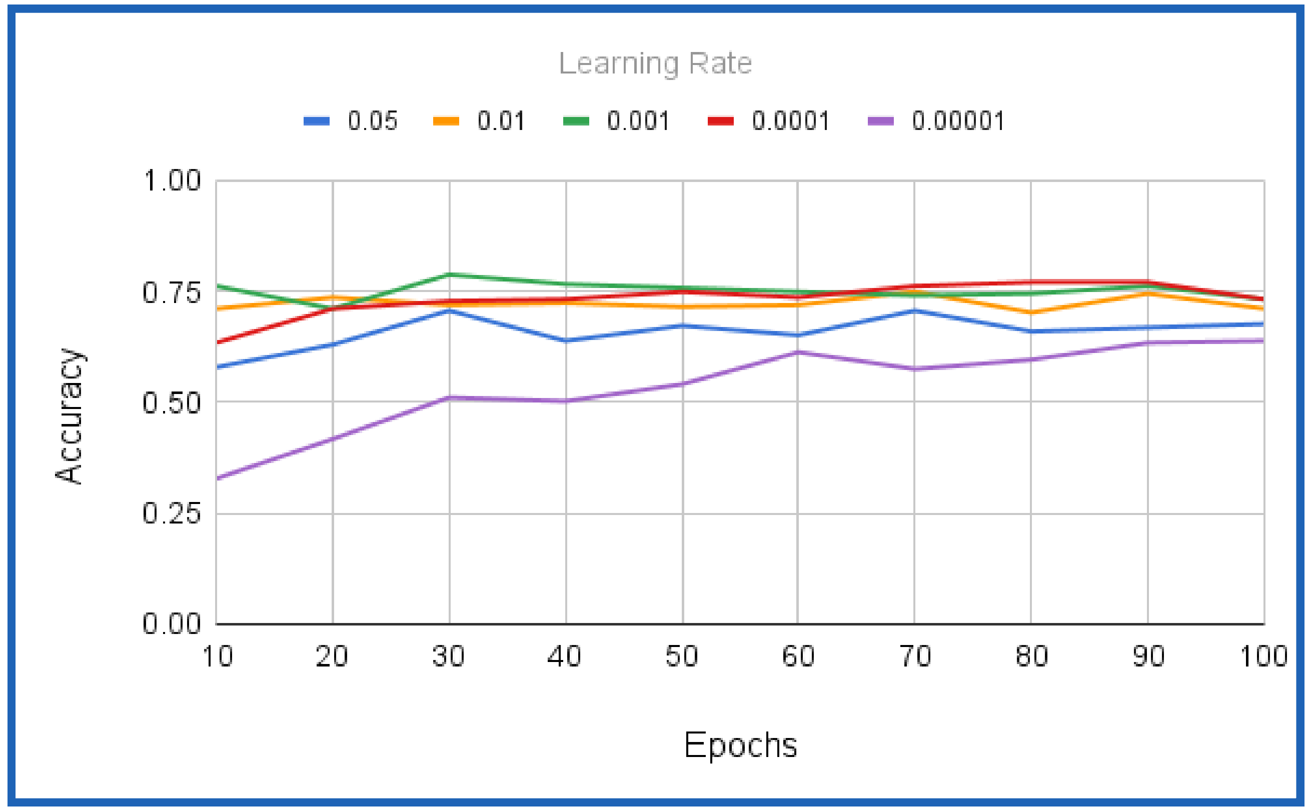

Figure 8. MLP: Validation accuracy vs. epochs for different learning rates.

- out of the different deep learning models tested, MLP performed the best
  - MLP was then integrated into the web app
- 50 experiments were performed by varying the learning rates between 0.0001 and 0.01, and epochs between 10 and 50
- Best validation accuracy of 78.72% was achieved at a learning rate of 0.001 with 30 epochs

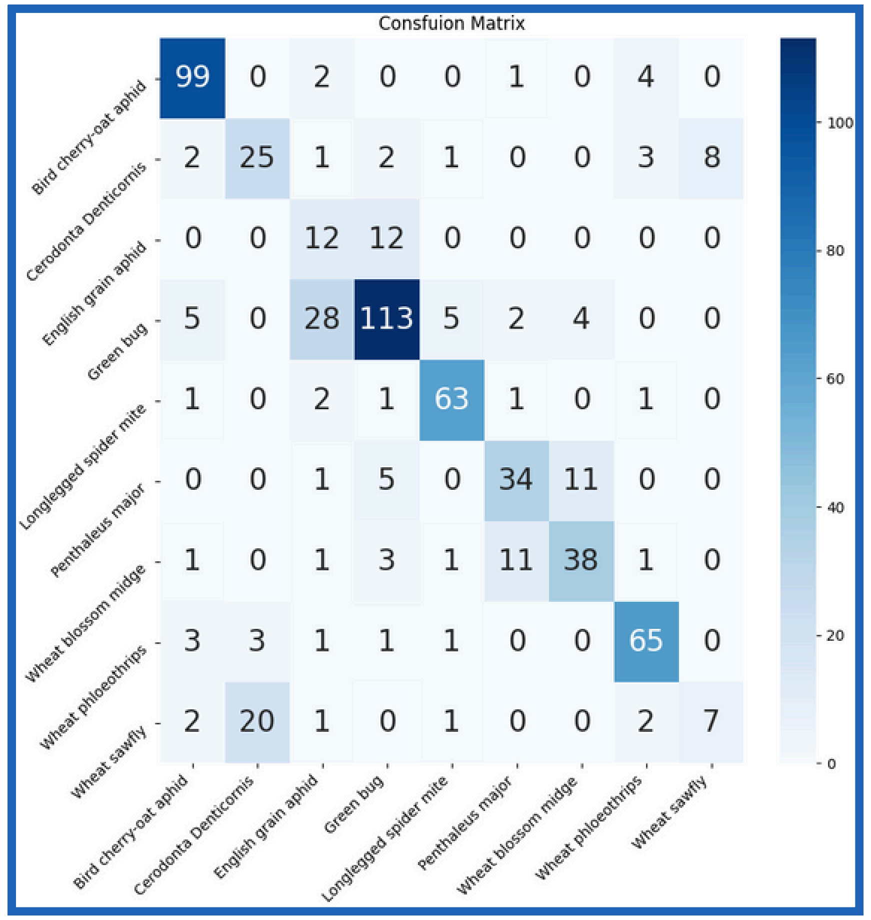

Figure 9. MLP: Confusion matrix of test results

- Test accuracy of 74.51%
- Wheat sawfly and English grain aphid are the worst-performing categories
  - Wheat sawfly was correctly identified for only ~47% of the images
  - English grain aphid was correctly identified for only 50% of the images

Conclusion

- Effectively developed a deep-learning model for wheat pest detection & web application to provide farmers with:
  - real-time pest identification
  - targeted pest-removal suggestions
- Can help mitigate crop loss in the early stages of wheat crop pest infestation
- This AI-driven tool can be deployed in wheat crop fields
  - Low-cost, easy to use, efficient, convenient, & has remote monitoring capability
  - Eliminates the need for manual pest monitoring
- Advantages of the device/web app:
  - Better wheat pest management may lead to less economic loss and better food security

Limitations & Future Studies

- Image resolution is not ideal
  - Prediction accuracy can be improved with better image quality
- Multiple devices (cameras) needed for a large wheat field
  - Future study: use drone camera with better image resolution
- User needs to initiate pest detection
  - Future study: Continuous pest monitoring and notification alerts; mobile app development

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