Zimbabwe's higher education landscape. Many students face economic, social, and psychological pressures that affect their academic success. Data-informed advising and peer mentoring – when grounded in empathy and local cultural values – help identify at-risk learners early and provide tailored interventions. Community-based mentorship, where senior students or alumni guide juniors, can foster belonging and motivation even in virtual spaces.

Overall, adapting this QA framework to Zimbabwe ensures that quality becomes a lived and equitable experience rather than a theoretical standard. By aligning pedagogy, technology, and support systems with the realities of Zimbabwean students – balancing innovation with accessibility – the framework redefines quality assurance as a process of inclusion, engagement, and locally grounded continuous improvement [7].

**Conclusion.** The integration of agile pedagogy, digital ecosystems, and student-centered support redefines QA for online engineering education. By embedding engagement metrics into quality assurance systems, institutions can achieve continuous improvement that resonates with Generation Z learners. The framework accentuates the need for adaptability, empathy, and data-driven decision-making in QA processes. Future research should focus on pilot testing this model across engineering faculties to assess scalability, cost-effectiveness, and cultural adaptability in developing contexts such as Zimbabwe.

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## AI AND COMPUTER VISION-BASED PEST AND DISEASE DETECTION FOR GREENHOUSE CROPS IN ZIMBABWE

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**Abstract.** Pests and diseases remain a major constraint to agricultural productivity in Zimbabwe, causing significant losses and limiting farmers' income. In greenhouse farming, early detection of infestations is critical to ensure healthy crops and reduce pesticide overuse. This study presents a computer-vision system powered by artificial intelligence (AI) for early identification of common pests and diseases in greenhouse crops. A convolutional neural network (CNN) trained on a regionally curated dataset of healthy and diseased plant images automatically classifies visual symptoms from digital photographs. The system is implemented through a MATLAB desktop application, enabling offline classification for users with limited internet access. The CNN achieved 83 % training accuracy and 82 % validation accuracy, with high precision and recall across multiple crop categories. Testing confirmed reliable detection of leaf curl, septoria leaf spot, and related infections in tomatoes and peppers. This work demonstrates that locally trained deep-learning models can effectively support greenhouse farmers in Zimbabwe, enhancing early response and minimizing losses due to pest and disease outbreaks.

**Keywords:** AI, computer vision, pest detection, CNN, greenhouse farming, image classification.

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**Introduction.** Agriculture forms the economic backbone of Zimbabwe, providing livelihoods to more than 60 % of the population (FAO, 2020). Greenhouse farming is expanding as a response to drought and erratic rainfall (Chikulo, 2020), offering a controlled environment for year-round production. However, these enclosed systems are prone to rapid pest and disease spread (Mutambara, 2021), and manual inspection methods are time-consuming and inconsistent. Recent advances in artificial intelligence and deep learning allow visual recognition of plant stress directly from images. Studies by Mohanty et al. (2016) and Ferentinos (2018) show that CNNs can classify plant diseases with >90 % accuracy. Yet, many of these systems are trained on datasets from other regions and may fail under African conditions. This work proposes a localized AI tool for Zimbabwean greenhouses, combining CNN-based pest recognition with a simple MATLAB graphical interface to promote accessibility and reduce dependence on cloud computing.

**Materials and Methods.** Images were sourced from PlantVillage and Kaggle, covering tomatoes, cucumbers, onions, potatoes, lettuce, and peppers. Both healthy and diseased samples were included. Images were resized to 224 × 224 pixels, normalized, and augmented by random rotation, flipping, and brightness adjustment to improve model generalization. A custom Convolutional Neural Network consisting of convolution, ReLU, pooling, and fully connected layers was trained using the Adam optimizer with categorical cross-entropy loss. The dataset was split 80:20 for training and validation. Performance metrics included accuracy, precision, recall, and F1-score, computed from the confusion matrix (Fig. 1). To enhance usability, a MATLAB App Designer graphical user interface was developed (Fig. 2). Users can upload an image, trigger classification, and receive instant feedback on crop health status. The application runs offline and is optimized for low-specification computers commonly available to smallholder farmers.

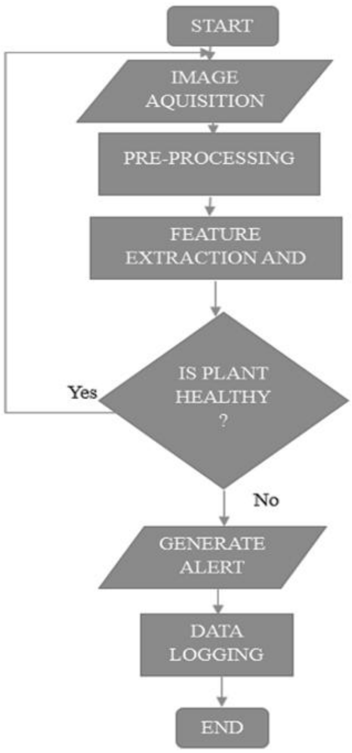


Figure 1 – System flowchart

**Results and Discussion.** The CNN achieved 83.10 % training and 82.15 % validation accuracy, demonstrating effective learning despite limited image diversity. Precision and recall values exceeded 80 % for most disease categories, confirming the model's diagnostic reliability. Random testing produced 100 % accuracy on sample batches, verifying consistency. The MATLAB GUI accurately classified all tested crop images, with users reporting an intuitive interface. Localization of datasets proved critical: using Zimbabwe-specific crops improved detection accuracy under regional lighting and humidity conditions. Data augmentation techniques further strengthened the model's robustness against image variations. However, limitations persist–class imbalance, uneven lighting, and lack of embedded real-time deployment restrict field scalability. Future work will integrate low-cost cameras and IoT modules for continuous greenhouse monitoring.

**Conclusion.** This project demonstrates a low-cost, AI-driven vision system capable of detecting and classifying common pests and diseases affecting greenhouse crops in Zimbabwe. The integration of a CNN model with an offline MATLAB GUI offers a practical decision-support tool for local farmers, reducing reliance on manual inspection and enabling early intervention. Continued expansion of region-specific image datasets and deployment on embedded hardware will further improve reliability and real-time performance, advancing sustainable greenhouse production across Zimbabwe.

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