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AI-Powered Image Recognition for Early Detection of Pests in Medicinal Crops

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A B S T R A C T

Artificial intelligence-based computer vision offers a practical approach to field-scale crop-health monitoring, but its performance depends heavily on representative images and consistent annotations. This study developed and evaluated a bounding-box detection workflow for four field-observed classes in lemongrass (*Cymbopogon citratus*): grasshopper insects, holes consistent with grasshopper feeding, *Curvularia*-like reddish spots, and *Fusarium*-like long reddish stripes. Images were collected under natural field conditions, grouped through visual examination and expert- and literature-assisted assessment, annotated with class labels and bounding boxes, and divided into training, validation, and test subsets at an 80:10:10 ratio. The test visualization showed detection of the single grasshopper instance, the single *Curvularia*-like instance, 20 of 21 annotated feeding-hole instances, and 16 of 17 *Fusarium*-like instances; one additional hole-like object was detected although it had not been annotated. Mean confidence exceeded 0.50 in every class, with the highest confidence for feeding-hole symptoms and the lowest for *Curvularia*-like spots. These findings demonstrate the feasibility of using field images for early symptom recognition. Larger independently validated datasets and confirmed pathogen diagnoses are required before deployment in a farmer-facing mobile application.

Contribution to Sustainable Development Goals (SDGs):
SDG 2 – Zero Hunger
SDG 9 – Industry, Innovation and Infrastructure
SDG 12 – Responsible Consumption and Production
SDG 13 – Climate Action

1. INTRODUCTION

Artificial intelligence (AI) and machine learning are increasingly used in agricultural production systems to support monitoring, prediction, and decision-making [1], [2]. Their applications extend to crop management, soil and water monitoring, disease diagnosis, yield estimation, and supply chain operations [3]. In crop protection, image-based AI can help localize visible symptoms and potentially support earlier intervention before damage becomes severe [4], [5].

Accurate identification remains central to integrated pest management because an incorrect diagnosis may lead to ineffective treatment, unnecessary pesticide use, and avoidable environmental costs [6], [7]. Recent computer vision approaches have shown promising performance in detecting and classifying plant pests and diseases [8]–[10]. Nevertheless, reported performance is often evaluated on controlled images with uniform backgrounds, whereas farmer-generated images are affected by variable lighting, viewing angles, occlusion, symptom severity, and background complexity.

The availability and quality of field images are therefore decisive. PlantDoc demonstrated that non-laboratory images can substantially improve the relevance of plant-disease recognition models for real-world settings [11]. Similarly, recent agricultural AI frameworks emphasize that diverse and accurately labelled datasets are required for reliable deployment [12]. This requirement is particularly important for medicinal crops, which are underrepresented compared with major food crops in public computer vision datasets.

Lemongrass and related *Cymbopogon* crops may be affected by chewing insects and fungal leaf symptoms that reduce usable biomass and potentially compromise essential-oil production. A field-oriented detection workflow could assist farmers in documenting symptoms and prioritizing expert consultation. However, model outputs should be interpreted as decision-support information rather than definitive pest or pathogen diagnosis.

This study addresses the practical gap between controlled-image research and field implementation by using images captured under natural cultivation conditions. The contribution is methodological: it documents image collection, symptom grouping, bounding-box annotation, dataset splitting, and preliminary test-set interpretation for a medicinal crop.

The study aimed to develop and evaluate a field-image object-detection workflow for recognizing four pest and disease-symptom classes in lemongrass and to report detection outcomes and confidence scores consistently with the visualized data. Because the available dataset is exploratory, the study does not claim clinical-style diagnosis, species-level pathogen confirmation, or generalizable production accuracy.

2. RESEARCH METHOD

This exploratory study used field observation and image documentation. Plant images were captured in cultivated plots using mobile-device cameras under naturally varying lighting, distance, angle, and background conditions. The workflow consisted of image collection, symptom-class definition, bounding-box annotation, model training, validation, and test-set evaluation.

2.1. Image Data Collection

Images were selected to represent variation in object position, leaf orientation, symptom size, symptom colour, and background complexity. Blurred or unusable images were excluded. The medicinal plant material used in this study is lemongrass (*Cymbopogon citratus*).

2.2. Symptom-Class Definition and Biological Verification

The obtained photos were sorted by symptom similarity, and the cause of the symptoms was identified. Identification is carried out by comparing with the literature or asking experts. This process can also use relevant features and focus on symptomatic areas [15]. Precise information about the cause of the symptoms will help ensure the algorithm works appropriately.

2.3. Image Annotation

Each target object or symptom area was marked with a class label and a rectangular bounding box. Bounding boxes provide the spatial ground truth required for object-detection models to learn both object location and class. Label consistency was checked manually before the images were divided into model-development subsets.

2.4. Model Development and Evaluation

The annotated images were processed using an object-detection pipeline that generated localized bounding boxes, class labels, and confidence scores, which are the outputs expected from modern object detectors [13]. The dataset was divided into 80% training, 10% validation, and 10% testing. Detection outcomes were summarized as detected, not detected, or detected without an existing ground-truth tag. Confidence scores were summarized by class.

3. RESULT AND DISCUSSION

The field-image dataset comprised four recognition classes: grasshopper insects, holes consistent with grasshopper feeding, *Curvularia-like* reddish spots, and *Fusarium-like* long reddish stripes (Figure 1). The examples illustrate the difference between field images and annotated model outputs. The use of natural backgrounds increases practical relevance but also introduces variability in lighting, scale, and occlusion that may reduce model stability.

Grasshopper-related damage appeared as irregular holes and missing leaf tissue, consistent with chewing injury. The *Curvularia-like* class showed localized reddish-to-brown lesions or spots. Published studies have confirmed the presence of *Curvularia* species on *Cymbopogon citratus* and described leaf-blight lesions on affected plants [15], [16]. The fourth class consisted of long, reddish, stripe-like symptoms, provisionally labelled *Fusarium-like*. Because the study did not include laboratory confirmation, the model should be understood as recognizing image patterns, not identifying pathogens etiologically.

The model detected the single test instance of a grasshopper and the single *Curvularia-like* instance. For the feeding-hole class, 20 annotated instances were detected, and one annotated instance was missed. For the *Fusarium-like* class, 16 instances were detected, and one was missed. Thus, *Fusarium-like* symptoms were predominantly detected rather than predominantly undetected. The model also produced one hole-like detection for an object that had not been included in the ground-truth annotation. This result was retained as “detected without tagging” rather than automatically treated as a true positive. It may represent either an omitted annotation or a false-positive prediction and should be independently adjudicated during annotation quality control.

Figure 2 summarizes the detection outcomes for each recognition class. Overall, the object detection model successfully identified most annotated objects across the four categories. The grasshopper and Curvularia-like classes each contained a single test instance, both of which were correctly detected. For feeding-hole symptoms, 20 of the 21 annotated objects were detected; one was missed, and one additional object was detected without a corresponding annotation. Similarly, the model detected 16 of the 17 annotated Fusarium-like symptoms. These results indicate that the proposed workflow is capable of recognizing visible pest and disease symptoms under natural field conditions, although annotation completeness and dataset size remain important factors influencing performance.

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a. Before Tagging b. After Tagging

A. Symptoms of Grasshopper Attack

a. Before Tagging b. After Tagging

B. Symptoms of Grasshopper Attack

a. Before Tagging b. After Tagging

C. Symptoms of *Culvilaria* sp Attack

a. Before Tagging b. After Tagging

D. Symptoms of *Fusarium* sp Attack

Fig. 1. Symptoms of Pest Attack of Citronella Plant Diseases.

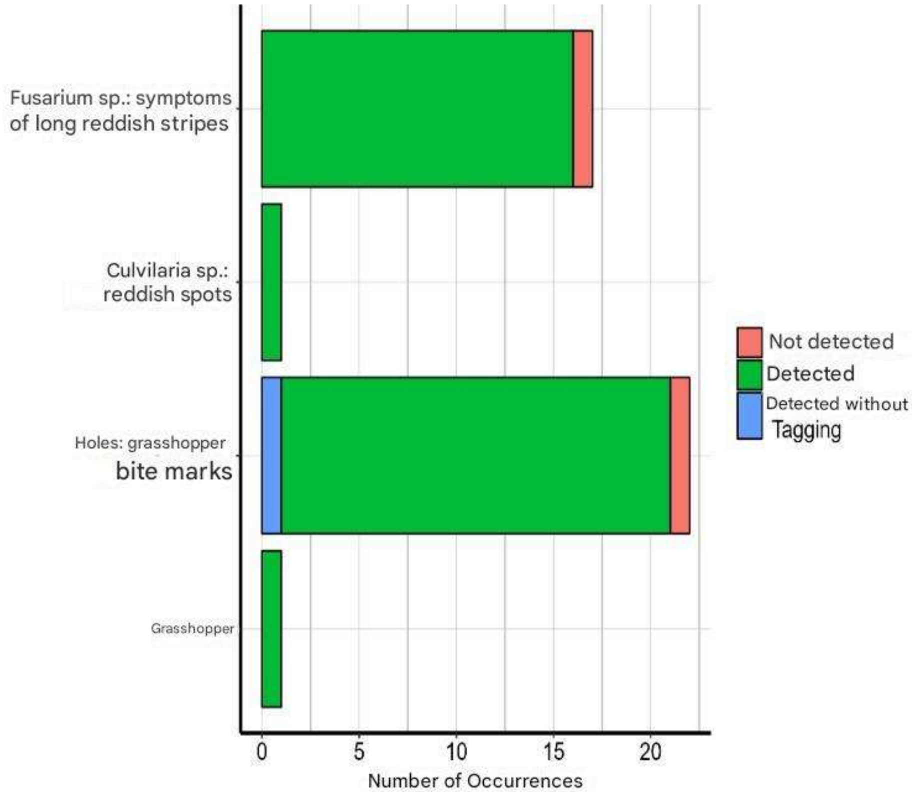

Fig. 2. Data Accuracy Level.

While the detection counts describe how many objects were successfully recognized, the confidence scores provide additional information about the certainty of each prediction. Figure 3 presents the distribution of confidence values for the four recognition classes. Higher confidence values generally indicate stronger agreement between the learned image features and the predicted class, whereas lower values suggest greater uncertainty due to symptom variability, complex backgrounds, or limited training samples. The mean confidence score exceeded 0.50 for all four classes (Figure 3).

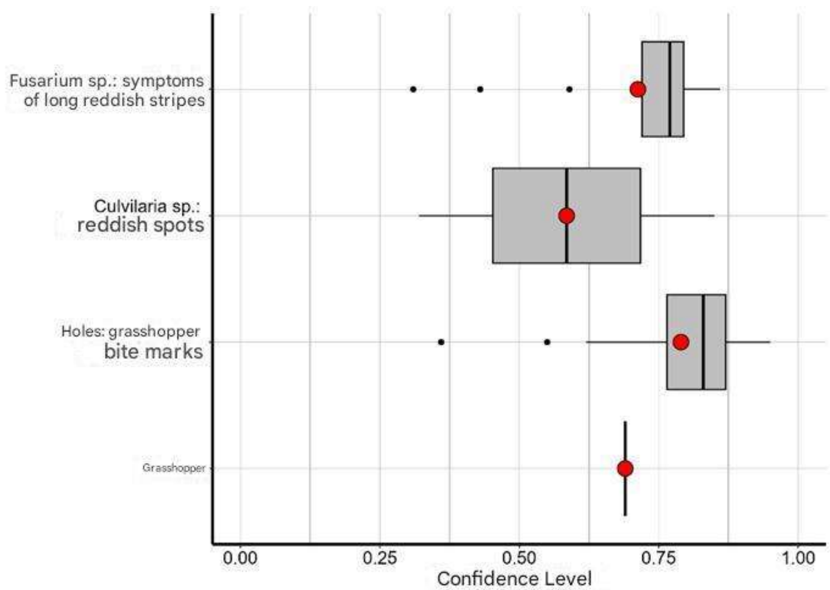

Fig. 3. Algorithmic Confidence Level.

The feeding-hole class showed the highest average confidence, whereas the *Curvularia-like* class showed the lowest and widest distribution. Confidence is not equivalent to accuracy and should not be interpreted as a calibrated probability of correctness; modern neural networks can be overconfident or poorly calibrated [14]. The very small also makes percentage-based claims unstable. Additional field images, independent test

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data, balanced class representation, and standard metrics such as precision, recall, F1-score, intersection over union, and mean average precision are required for a robust performance assessment.

4. CONCLUSION

This study provides a proof of concept for field-image-based object detection of pest and disease symptom patterns in a medicinal *Cymbopogon* crop. The results show successful detection of most annotated test instances across the four classes, including 16 of 17 *Fusarium-like* instances.The findings should nevertheless be interpreted cautiously because the test set was small, fungal causes were not laboratory-confirmed. Future work should expand the dataset across seasons and locations, validate annotations with plant pathologists and entomologists, report standard object-detection metrics, and test the model prospectively before integration into a mobile advisory application.

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