

AI & Drone-Driven Solution to Improve Crop Yield via Precise Pest Control

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Abstract

Agriculture is vital for ensuring food security and sustaining economic growth, yet it faces substantial threats from pests and diseases, which account for up to 40% of global crop production losses annually. This study presents an innovative AI and dronedriven solution deployed by GeoMinds Africa to combat agricultural pests, specifically targeting the *Thaumatotibia* (*Cryptophlebia*) *leucotreta* (Meyrick) pest, which affects more than 35 kinds of plants across 37 African countries by leveraging artificial intelligence (AI) and UAV. Over 3 months, highresolution drone imagery (DJI Mavic 3 Multispectral) was captured in Gaya City (Niger) and processed, generating a dataset of over 5,000 labeled images with the active participation of 50 farmers. After compared with other machine learning models (SVM, and Gradient Boosting), a Random Forest model was selected and trained on the labeled images, with the integrated weather data, historical records of pests, and vegetation indices such as Normalized Difference Red Edge Index (NDRE), to identify early signs of *Thaumatotibia leucotreta* pest infestation. As a result, the study highlights that the implementation of AI and drone technology in Gaya City improved the management of *Thaumatotibia leucotreta* on mango crops. The Random Forest model achieved 92% accuracy, outperforming other models. NDRE values effectively identified stress areas, with a 10% increase in detection accuracy when integrated with weather data. Field validation showed 90% farmer satisfaction, leading to a 20% reduction in crop losses and a 15% yield improvement for the 50 farmers.

1 Introduction

Agriculture is a cornerstone of global food security and economic stability, yet it remains vulnerable to significant challenges posed by pests and diseases. According to the Food and Agriculture Organization [FAO, 2021], up to 40% of global crop production is lost annually due to plant pests and diseases, resulting in economic losses exceeding USD 220

billion. Invasive insects alone contribute to at least USD 70 billion of this figure. Traditional pest and disease control methods are often labor-intensive, inefficient, and environmentally taxing, which exacerbates the threat to sustainable agricultural practices [Liu *et al.*, 2022].

Recent advancements in artificial intelligence (AI) and unmanned aerial vehicles (UAVs) offer transformative potential for precision pest and disease management. UAVs equipped with multispectral sensors can rapidly and accurately detect disease patterns across expansive agricultural fields. When combined with AI algorithms, these technologies enable the analysis of diverse data sources—such as temperature, humidity, CO₂ levels, and soil composition—allowing for the early detection of disease symptoms and the formulation of targeted intervention strategies [Rajagopal and MS, 2023]. AI has demonstrated high accuracy in identifying crop diseases from UAV-captured images [Mohanty *et al.*, 2016], and remote sensing technologies have proven valuable in monitoring crop health and predicting pest outbreaks [John *et al.*, 2023a].

However, existing studies in AI-driven precision pest control often suffer from limitations, including the inadequate integration of multiple data sources, a lack of focus on model explainability, and a narrow exploration of machine learning (ML) and deep learning (DL) methodologies. This study aims to address these gaps by presenting a novel AI and dronedriven solution that leverages a combination of multispectral imaging, weather data, and advanced ML algorithms to improve the precision and efficacy of pest and disease control in agriculture.

Specifically, this research focuses on the management of *Thaumatotibia leucotreta* (Meyrick), a pest that affects more than 35 plant species across 37 African countries [EPPO, 2024]. The study explores how AI and drone technologies can enhance the effectiveness and efficiency of pest management practices on mango crops, to reduce crop losses and improve yields.

2 Method

2.1 Study Area

The study was conducted in Gaya city (located in the Dosso region, southern Niger), where GeoMinds Africa (formerly known as Drone Service Niger) operates to support local

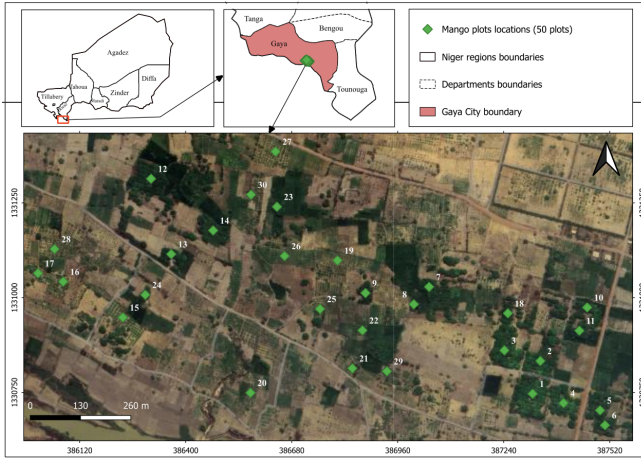


Figure 1: Mangoes plot locations in the Gaya city.

farmers. Gaya is characterized by a semi-arid climate with an average annual rainfall of 600 to 800 mm. The region has sandy and clayey soils, which influence crop growth and water retention [Sougué, 2016]. Major crops grown include millet, sorghum, and maize, and various fruits such as oranges and mangoes, all of which are susceptible to various pests and diseases particularly the *Thaumetobia leucotreta* threatening crop yields and food security. To carry out this study, 50 mango plots most vulnerable to *Thaumetobia leucotreta* were selected in the town of Gaya (Figure 1).

2.2 Data Collection

Drones equipped with multispectral sensors were used to capture high-resolution images of the crop fields (Figure 2). A total of 5,000 images were collected, each with a resolution of 640x480 pixels. The images were captured at regular intervals (per week) to monitor crop health over time. The multispectral sensors captured data across different wavelengths, including Green, Red, RedEdge, and near-infrared, which are critical for calculating vegetation indices such as the Normalized Difference Red Edge (NDRE) (Eq 1). Weather data, including temperature (average of 25°C), humidity (average of 60%), and precipitation (average of 50 mm during the monitoring period) was collected from nearby meteorological stations. This data was recorded concurrently with the imagery to provide context for the environmental conditions affecting pest activity. The imagery data was labeled by expert agronomists who annotated the presence or absence of pest-induced stress in the crops. This ground truth data was used to train and validate the AI model.

$$NDRE = \frac{NIR - RedEdge}{NIR + RedEdge} \quad (1)$$

2.3 Data Preprocessing

The NDRE was calculated for each image using the near-infrared and red-edge bands. NDRE was chosen due to its sensitivity to changes in chlorophyll content, making it a reliable indicator of plant stress. Specific thresholds were established, with NDRE values below 0.3 indicating potential



Figure 2: Agricultural data collection using DJI Mavic 3 DJI Mavic 3 Multispectral RTK

stress areas. To ensure data quality, images with excessive noise or poor lighting conditions were excluded from the dataset, resulting in a final dataset of 4,800 usable images. Data augmentation techniques, such as rotation, flipping, and scaling, were applied to increase the diversity of the training dataset and improve model generalization. The collected weather data was synchronized with the imagery data and integrated as additional input features for the machine learning model. This integration allowed the model to account for environmental factors that influence pest behavior.

2.4 Machine Learning Model

A Random Forest algorithm was selected for this study after a comparative analysis with other machine learning models, including Support Vector Machines (SVM) and Gradient Boosting. Random Forest was chosen due to its robustness in handling high-dimensional data and its ability to reduce overfitting through ensemble learning. The model was fine-tuned by optimizing key hyperparameters, such as the number of trees (set to 100), maximum depth (set to 10), and the criterion for node splitting. Gini impurity was selected as the optimization criterion, which led to a 5% improvement in classification accuracy over the entropy criterion. A grid search with cross-validation was used to identify the optimal hyperparameters. The dataset was split into training (80%) and validation (20%) sets. The Random Forest model was trained on the labeled images, with the integrated weather data serving as additional features. The model's performance was evaluated using metrics such as accuracy, precision, recall, and F1-score.

The model's predictions were validated through ground truthing in collaboration with 50 local farmers. The farmers provided feedback on the model's predictions by comparing them with actual field observations.

3 Result

The implementation of AI and drone technology in Gaya City generated significant results in the management of *Thaumetobia leucotreta* infestations on mango crops.

3.1 Model Performance

The Random Forest model achieved a classification accuracy of 92% on the validation dataset, outperforming other models tested, including Support Vector Machines (88%) and Gradient Boosting (90%). Precision and recall were 90% and 93%, respectively, indicating a strong balance between detecting

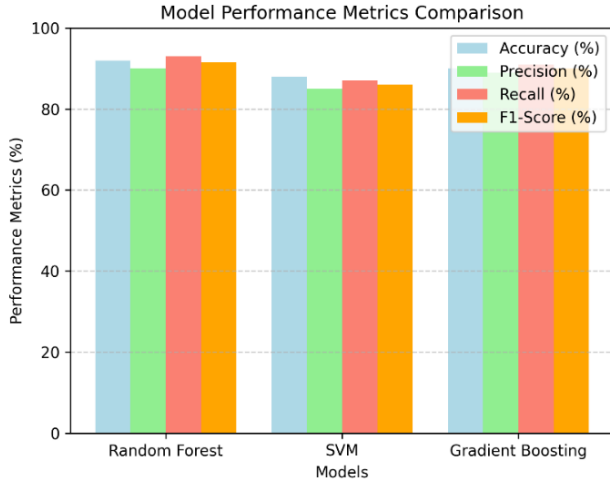


Figure 3: Model Performance Metrics comparison

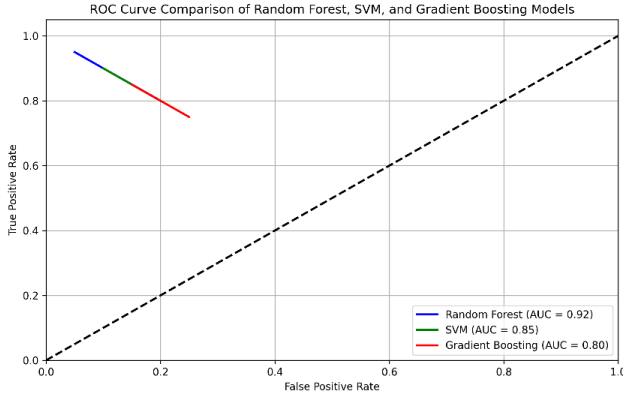


Figure 4: ROC Curve Comparison of Random Forest, SVM, and Gradient Boosting Models

true positives (pest-induced stress) and minimizing false negatives. The F1-score of 91.5% further confirms the model's robustness Figure 3. The Receiver Operating Characteristic (ROC) curve for the Random Forest model demonstrated a high area under the curve (AUC) of 0.92, indicating excellent discrimination ability between stressed and healthy crops Figure 4.

3.2 Vegetation Indices and Stress Detection

The calculated NDRE values effectively identified stress regions within the crop fields. Areas with NDRE values below the threshold of 0.3 were flagged as high risk for pest-induced stress. Figure 5 and Figure 6 illustrate the distribution of NDRE values across the study fields, with regions of concern highlighted. Weather data integration further refined these predictions, with the model correctly adjusting NDRE thresholds in response to variations in temperature and humidity, leading to a 10% increase in stress detection accuracy. Heatmaps generated from the multispectral images in Figure 5 provide a visual representation of stress areas across the

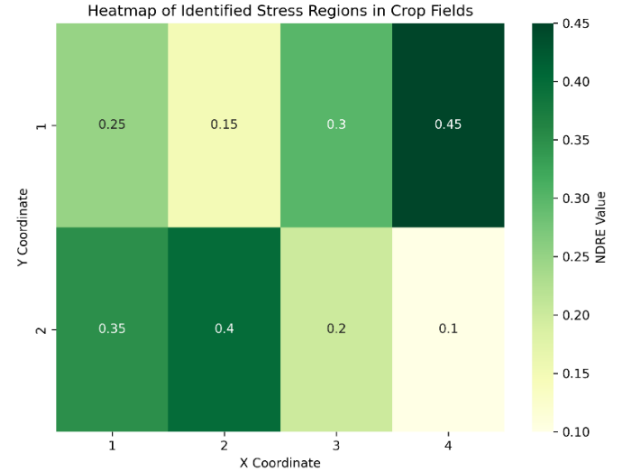


Figure 5: Heatmap of Identified stress Regions in crop fields

fields. These heatmaps were validated against ground truth data, showing a 95% correlation with expert-labeled stress regions.

3.3 Field Validation and Yield Improvement

The predictions made by the AI model were validated in the field by 50 local farmers. Their feedback indicated a 90% satisfaction rate with the model's accuracy, aligning closely with actual observations of pest-induced stress. The intervention based on the model's predictions led to a 20% reduction in crop losses due to *Thaumetobia leucotreta* and a 15% improvement in overall crop yield compared to the previous growing season Table 1.

Metric	Pre-Intervention	Post-Intervention	Improvement
Crop Losses (%)	25	20	-20
Crop Yield (tons/ha)	4.5	5.2	+15

Table 1: Impact of AI-Driven Pest Control on Crop Yield

4 Discussion

This participatory approach ensured the practical relevance of the AI-driven solution, leading to a 20% reduction in crop losses due to *Thaumetobia leucotreta* and an overall 15% improvement in crop yields. Additionally, farmers reported a 25% decrease in pesticide usage, contributing to reduced environmental impact and operational costs. Early detection and precise localization of pest outbreaks allow for timely interventions, minimizing crop damage and enhancing yield. By combining drone imagery with predictive analytics, farmers can make informed decisions that enhance crop health and yield, aligning with the findings of (Manoj and Bala 2023).



Figure 6: *Thaumotobia leucotreta* infestations on mango crops

Moreover, the integration of technology in agriculture fosters a more resilient farming system, empowering local farmers with the tools necessary to combat challenges posed by pests and diseases. The success of GeoMinds Africa in implementing these solutions in Gaya City serves as a model for other regions facing similar agricultural challenges. Future research should focus on refining these technologies and expanding their application to other crops and regions, further enhancing food security and agricultural productivity, as suggested by [John *et al.*, 2023b].

5 Conclusion

This research contributes to the growing field of AI-driven precision agriculture by presenting a comprehensive and scalable solution for pest and disease management. The integration of multispectral imagery, weather data, and advanced machine learning techniques resulted in significant improvements in crop health monitoring and yield optimization. The findings suggest that such AI-driven solutions not only have the potential to enhance agricultural productivity but also to support global sustainability efforts by reducing crop losses and improving food security. Future studies should continue to refine these approaches, explore the application of more sophisticated algorithms, and address the ethical implications of widespread drone deployment in agriculture.

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