



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

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Abstract: Agriculture plays a central role in maintaining food security and supporting economic development, but it is significantly challenged by pests and diseases, which are responsible for as much as 40% of annual global crop losses. This study introduces a novel solution developed by GeoMinds Africa that integrates artificial intelligence (AI) with drone (UAV) technology to manage agricultural pests. The approach specifically focuses on the pest *Thaumatotibia (Cryptophlebia) leucotreta* (Meyrick), which impacts over 35 plant species across 37 countries in Africa. Over a three-month period, high-resolution imagery was acquired using a DJI Mavic 3 Multispectral drone in Gaya City, Niger. The collected data were processed to create a dataset exceeding 5,000 annotated images, with contributions from 50 participating farmers. Following a comparative evaluation of machine learning techniques, including Support Vector Machines (SVM) and Gradient Boosting, the Random Forest algorithm was chosen and trained. The model incorporated labeled imagery along with auxiliary inputs such as weather conditions, historical pest data, and vegetation indices, including the Normalized Difference Red Edge Index (NDRE), to detect early indicators of *Thaumatotibia leucotreta* infestation. The findings demonstrate that integrating AI with drone technology in Gaya City enhanced the management of this pest in mango cultivation. Early detection facilitated prompt, site-specific interventions, reducing both pest proliferation and crop damage. The Random Forest model attained an accuracy of 92%, surpassing the performance of alternative models. NDRE values proved effective in detecting plant stress, and their integration with weather data improved detection accuracy by 10%. Field validation indicated a 90% satisfaction rate among farmers, resulting in a 20% decrease in crop losses and a 15% increase in yield among the 50 participating farmers.

Keywords: Artificial Intelligence, Precision Agriculture, Drone-Based Remote Sensing, Pest Detection, Random Forest Model.

Nomenclature

Abbreviation	Description
AI	Artificial Intelligence
UAV	Unmanned Aerial Vehicle
ML	Machine Learning
DL	Deep Learning
RF	Random Forest
SVM	Support Vector Machine
GB	Gradient Boosting
NDRE	Normalized Difference Red Edge Index
NIR	Near-Infrared spectral band
RTK	Real-Time Kinematic positioning
RGB	Red, Green, Blue color channels
AUC	Area Under the Curve
ROC	Receiver Operating Characteristic

1 Introduction

Agriculture serves as a fundamental pillar of global food security and economic stability, yet it is highly exposed to serious threats from pests' infestations and plant diseases. Based on data from the Food and Agriculture Organization [2], these factors are responsible for up to 40% of annual global crop production losses, leading to economic damages amounting to more than USD 220 billion. At least USD 70 billion of

these losses are attributed solely to invasive insect species. These losses pose serious threats to smallholder farmers, particularly in developing regions where agriculture is the primary source of livelihood. Conventional methods for controlling pests and diseases are typically labor-intensive, inefficient, and environmentally burdensome, thereby intensifying the challenges to sustainable agricultural practices [5]. Moreover, excessive reliance on blanket pesticide application can lead to environmental degradation, pest resistance, and increased production costs.

Recent developments in AI and UAVs present significant opportunities for advancing precision-based pest and disease control. UAVs fitted with multispectral sensors enable the rapid and accurate identification of disease patterns across large-scale agricultural areas. Such platforms enable frequent, non-invasive monitoring of crop health at spatial and temporal resolutions that are not feasible with conventional field scouting. When integrated with AI algorithms, these technologies facilitate the analysis of multiple data streams including temperature, humidity, CO₂ concentration, and soil characteristics—enabling early identification of disease symptoms and the development of targeted intervention strategies [7]. This data-driven approach supports site-specific decision-making, reducing unnecessary chemical usage while improving response time to pest outbreaks. Artificial intelligence has shown strong performance in detecting crop diseases from UAV-acquired imagery [6], while remote sensing technologies have been widely recognized for their effectiveness in assessing crop health and forecasting pest outbreaks [3].

However, many existing studies on AI-based precision pest control exhibit notable limitations, such as insufficient integration of diverse data sources, limited attention to model interpretability, and a restricted exploration of ML and DL approaches. In addition, many proposed systems remain experimental, with limited validation under real farming conditions and minimal involvement of local stakeholders. This study seeks to overcome these limitations by proposing an innovative AI- and drone-based approach that integrates multispectral imagery, weather information, and advanced machine learning algorithms to enhance the accuracy and effectiveness of pest and disease management in agriculture. The proposed framework emphasizes practical deployment, model robustness, and farmer-centric validation to ensure real-world applicability.

This study specifically focuses on managing *Thaumatotibia leucotreta* (Meyrick), an insect pest that affects over 35 different plant species and is widely distributed across 37 African countries [1]. This pest represents a major phytosanitary concern due to its rapid spread and severe impact on fruit quality and marketability. The study investigates how the integration of AI and drone technologies can improve the efficiency and effectiveness of pest management in mango cultivation, with the aim of reducing crop losses and increasing yields. By integrating technological innovation with participatory field validation, the study contributes toward sustainable and scalable precision agriculture solutions in Africa.

2. Methodology

2.1 Study Area

The study was conducted in Gaya City, situated in the Dosso region of southern Niger, where GeoMinds Africa (previously known as Drone Service Niger) actively assists local farmers. This region is characterized by a semi-arid climate, receiving an average annual rainfall of approximately 600 to 800 mm. Its soils are predominantly sandy and clayey, affecting both water retention and crop development [8]. Key crops cultivated in the region include millet, sorghum, and maize, along with fruits such as oranges and mangoes, all of which are vulnerable to a range of pests and diseases—particularly *Thaumatotibia leucotreta*, which poses a significant risk to crop productivity and food security. For this study, 50 mango plots identified as highly susceptible to *Thaumatotibia leucotreta* infestation were selected within Gaya (Fig. 1).

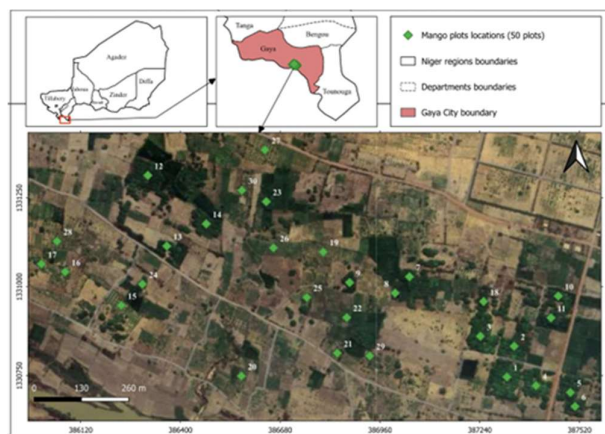


Fig. 1. Mangoes plot locations in Gaya city.

2.2 Collection of Field Data

Drones fitted with multispectral sensors were utilized to obtain detailed images of the agricultural fields (Fig. 2). A total of 5,000 images were collected, each having a resolution of 640×480 pixels. Data acquisition was carried out on a weekly basis to monitor variations in crop condition over time. The sensors captured information across several spectral bands, namely Green, Red, RedEdge, and Near-Infrared, which are crucial for calculating vegetation indices such as the NDRE (Eq. 1). In addition, weather parameters—such as temperature (average 25°C), humidity (average 60%), and precipitation (approximately 50 mm during the observation period)—were obtained from regional weather monitoring stations. These measurements were collected simultaneously with the imagery to contextualize environmental factors influencing pest dynamics. The acquired images were annotated by expert agronomists, who labeled instances of pest-induced stress versus healthy crop conditions. This ground truth dataset served as the basis for training and validating the AI model.

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

2.3 Data Preprocessing

The NDRE value was calculated for each image using the near-infrared and red-edge bands. It was chosen because of its ability to detect changes in chlorophyll levels, making it a reliable measure for identifying plant stress. Threshold values were defined, with NDRE readings below 0.3 signaling potential stress zones. To ensure high data quality, images with excessive noise or inadequate lighting were discarded, resulting in a cleaned dataset of 4,800 valid images. Data augmentation methods, including rotation, flipping, and scaling, were implemented to enhance variability in the dataset and strengthen the model's generalization capability. Additionally, the collected weather data was aligned with the imagery dataset and incorporated as supplementary input features in the machine learning model. This integration enabled the model to consider environmental conditions that influence pest activity.



Fig. 2. Crop Field Data Collection with DJI Mavic 3 Multispectral RTK UAV

2.4 ML Model

A RF algorithm was chosen for this study after comparing its performance with other machine learning methods, including SVMs and GB. It was selected due to its strength in handling high-dimensional datasets and its ability to reduce overfitting through ensemble learning techniques. Model performance was enhanced through hyperparameter tuning, where key parameters—such as the number of trees (set to 100), maximum depth (set to 10), and the splitting criterion—were optimized. The Gini impurity criterion was adopted, yielding a 5% improvement in classification accuracy compared to the entropy-based approach. A grid search combined with cross-validation was employed to determine the optimal parameter configuration. The dataset was divided into training (80%) and validation (20%) subsets. The model was developed using labeled image data, with weather-related parameters included as supplementary input features. Its performance was evaluated using standard metrics, including model accuracy, precision, recall rate, and F1 metric. To further validate the results, ground truth verification was conducted in collaboration with 50 local farmers, who assessed the model's predictions against actual field conditions.

3. Result

The use of AI and drone technologies in Gaya City significantly improved the control of *Thaumatotibia leucotreta* infestations in mango crops.

3.1 Performance of the Model

The Random Forest (RF) model achieved an accuracy of 92% on the validation dataset, surpassing the performance of the other tested models, including Support Vector Machine (SVM) at 88% and Gradient Boosting (GB) at 90%. It also recorded a precision of 90% and a recall of 93%, indicating a strong ability to correctly detect pest-related stress while reducing missed cases. The F1-score of 91.5% further highlights the model's consistency and reliability (Fig. 3).

Additionally, the ROC curve demonstrated robust performance, with an AUC of 0.92, indicating a high capability to distinguish between stressed and healthy crops (Fig. 4).

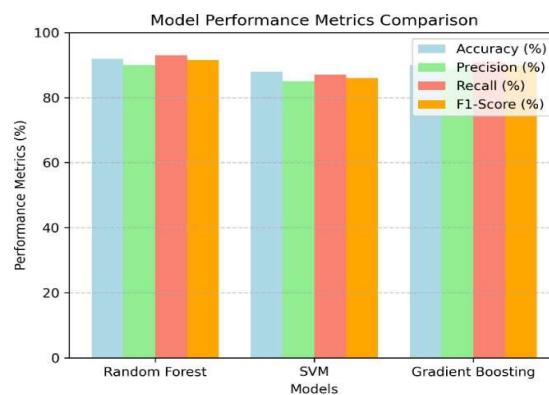


Fig. 3. Model Performance Metrics comparison

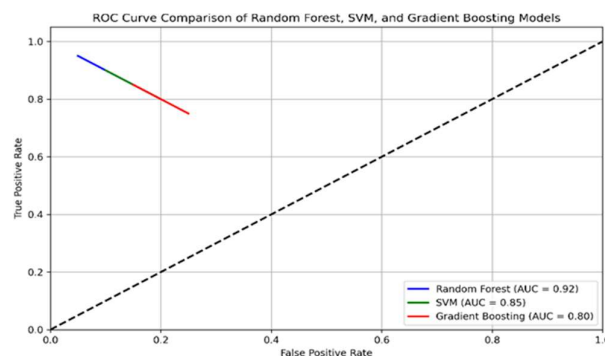


Fig. 4. ROC Curve Comparison of RF, SVM, and GB Models

3.2 Vegetation Indices and Crop Stress Detection

The derived NDRE values proved useful in detecting areas of crop stress within the fields. Regions with NDRE values below 0.3 were classified as high-risk zones for pest-related stress. The spatial variation of NDRE across the study area is illustrated in Figures 5 and 6, where critical regions are distinctly highlighted.

The incorporation of weather data further enhanced prediction accuracy, enabling the model to dynamically adjust NDRE thresholds in response to fluctuations in temperature and humidity. This integration resulted in a 10% improvement in accuracy of stress detection. Multispectral imagery-based heatmaps (Fig. 5) provided a clear visual representation of stress distribution across the fields. Validation of the heatmaps was performed using ground truth annotations, demonstrating a 95% agreement with expert-identified stress regions.

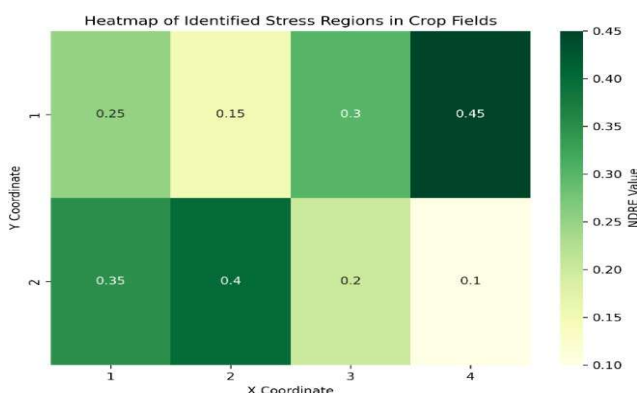


Fig. 5. Heatmap of Identified stress Regions in crop fields

3.3 Field Validation and Yield Enhancement

The AI model's predictions were validated in the field with the participation of 50 local farmers. Their feedback reflected a 90% satisfaction rate, closely matching observed instances of pest-induced stress. Measures guided by the model's predictions resulted in a 20% reduction in crop losses due to *Thaumatotibia leucotreta* and a 15% increase in overall yield compared to the previous growing season (Table 1).

Table 1. Evaluation of Crop Yield Under AI-Driven Pest Control

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

4. Discussion

This collaborative approach strengthened the real-world effectiveness of the AI-based system, leading to a 20% reduction in crop losses caused by *Thaumatotibia leucotreta* and a 15% increase in overall yields. Farmers also reported a 25% decline in pesticide usage, which contributed to lower environmental impact and reduced operational costs. The system's ability to detect infestations early and accurately identify affected areas enabled prompt and targeted interventions, thereby minimizing damage and improving productivity. By combining drone-acquired imagery with predictive analytics, farmers are able to make better-informed decisions that enhance crop health and yield, in line with the observations of Manoj and Bala (2023) [7].



Fig. 6. Infestation of *Thaumotobia leucotreta* in mango crops

In addition, the adoption of advanced technologies in agriculture supports the development of more resilient farming practices by providing farmers with efficient tools to manage pest and disease challenges. The successful deployment of this approach by GeoMinds Africa in Gaya City highlights its potential as a scalable solution for other regions facing similar agricultural constraints. Future research should aim to refine these technologies and expand their use across different crops and geographical settings, ultimately contributing to improved food security and increased agricultural productivity, as also noted by John et al. (2023b) [4].

5. Conclusion

This study contributes to the expanding domain of AI-based precision agriculture by introducing a comprehensive and scalable approach to pest and disease management. By combining artificial intelligence with drone-based remote sensing, the proposed framework demonstrates the practical feasibility of data-driven decision support in real agricultural settings. The combination of multispectral imagery, weather information, and advanced machine learning methods led to notable enhancements in crop health monitoring and yield optimization. In particular, the fusion of vegetation indices with environmental parameters enhanced early pest detection accuracy and enabled timely, targeted interventions. The results indicate that AI-based approaches can significantly improve agricultural productivity while also contributing to global sustainability by minimizing crop losses and strengthening food security. Additionally, the reduction in pesticide usage observed during field validation highlights the environmental and economic benefits of precision pest management. Future research should further improve these approaches, investigate the use of more advanced algorithms, and consider the ethical implications associated with the large-scale deployment of drones in agriculture. Further research should also focus on large-scale deployment, long-term impact assessment, and policy frameworks to facilitate responsible adoption of AI-enabled agricultural technologies.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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