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An Intelligent Deep Learning Framework for Automated Pest Detection in Coconut Trees

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Abstract : Rapid increase of pest associated yield losses in coconut plantations has led to the acute need for the development of scalable, accurate and field-ready diagnosis tools. Traditional manual methods of inspection are labor-intensive, subjective and are often inadequate for early detection of destructive pests such as the rhinoceros beetle larva, red palm weevils and eriophyid mites. To overcome this problem, an intelligent deep learning framework for automatic pest detection in coconut trees is proposed in this study, which takes advantage of a hybrid CNN-Transformer architecture, optimized for aerial imaging, taken using drones and aerial-based imaging devices. The model is equipped with advanced image augmentation, multi-scale feature extraction and localization using attention mechanism to make it more robust in complex plantation environment with occlusion, variable lightening conditions, and canopy density. Extensive experiments performed on a newly curated dataset of 14,250 annotated coconut tree pest images show that it can give superior performance (97.8% detection accuracy, 96.9% precision, 97.3% recall, and 0.98 mAP) as compared to ten state-of-the-art baselines. The results validate the potential of the framework to be used in real-time in precision agriculture systems, allowing early intervention and less pesticide use as well as better crop management. Concluding results show that intelligent pest detection through deep learning can be very beneficial for sustainable coconut farming and decision support capability for large-scale plantation monitoring.

Keywords: Deep learning, coconut pest detection, precision agriculture, convolutional neural networks, transformer models, aerial imaging, computer vision, pest classification, automated monitoring, smart farming

I INTRODUCTION

Coconut cultivation plays an important economic and cultural role in the tropical regions especially in India, Sri Lanka, Indonesia and the Philippines where it provides livelihood to millions of farmers and industries based on coconut-based products[1]. However, the productivity and sustainability of coconut plantations are currently under increasing threat from a variety of pests that are capable of causing severe damage to the palm canopy and nut production, as well as the long-term vitality of plantations. Pests like rhinoceros beetle (Oryctes rhinoceros), red palm weevil (Rhynchophorus ferrugineus), black headed caterpillar (Opisina arenosella) and eriophyid mite (Aceria guerreronis) are the most destructive and economic losses amounting to millions of dollars per year. Accurate and timely detection of these pests is of paramount importance as delay in diagnosis usually leads to rapid spread of infestation, rendering treatment more difficult, costly and environmentally damaging due to excessive use of pesticides[2].

The pest identification in coconut plantation has been done through manual inspection by skilled agricultural workers or extension officers. While effective under controlled circumstances, manual inspection is limited by a number of factors: it is slow, labor-intensive and susceptible to human error and is practically impossible on large-scale plantations or in remote farming areas. Moreover, pests are often small and hidden under fronds or are active at certain times making them difficult to detect with any regularity. The growing shortage of expert field personnel makes the challenge even more difficult and there is a need for automated and intelligent tools that can provide consistent performance at scale. With the recent development in computer vision and artificial intelligence, deep learning has become a powerful paradigm for solving complex agricultural monitoring tasks with high accuracy and low human intervention[3].

Researches in agricultural AI has shown considerable advancements of classification of leaf diseases, fruit countering and weed detection using convolution neural network (CNNs), recurrent architecture, attention mechanism and transformer based vision models. Yet, the field of automated pest detection in tree crops, and especially tall perennial crops such as coconut, has had little attention[4]. Coconut trees pose some of the challenges in 3D imaging because of their height, canopy structure and the variability in the environment. Pests tend to be in irregular shapes and in partially occluded areas and very cluttered natural backgrounds. These complexities require sophisticated feature extraction mechanisms that are able to extract both the global contextual information and fine details of local details. While the use of CNNs in agricultural image classification has proven to be very promising, these models cannot currently model long-range dependencies, particularly in environments with a high level of occlusion. Vision Transformers (ViTs) on the other hand offer better global attention and tend to need large datasets to prevent overfitting[5].

To overcome these limitations, recent works have attempted to overcome this issue by introducing CNN-based hierarchical feature extraction and Transformer-based attention modules. Such models have yielded good performance in the areas of monitoring of crops with drones and detection of small objects, which is the motivation to apply them in the area of detection of coconut pests. However, a dedicated and robust system that is made available specifically for the morphological peculiarities of the coconut pests and the plantation environments is still lacking. This is a gap to be addressed, and the need of such an integrated deep learning framework capable of accurate detection in the real world.

Research Problem: Coconut plantations do not have an automated, high-accuracy, early-warning system for the detection of multiple pest species in varied environmental conditions with a delayed intervention and tremendous crop loss

Research Question: How to build a hybrid deep learning framework for detecting pests robustly and with high precision in the coconut trees using real-time aerial and ground-level imagery? The major objectives of the study are as follow

- To design a smart deep learning model by integrating CNN and Transformers Network Architecture to detect Pests in a multi-class Setting for Coconut Plantation.
- To establish and process a large and annotated collection of pest images which can be used for aerial and ground applications.
- To validate the framework experimentally as compared to state-of-the-art models and to evaluate the performance for practical applications on agribusiness.

The organization of the study is as follows: Section 1 is the introduction of the background and motivation. Section 2 is a discussion on related work. The proposed methodology is described in Section 3. Experimental set up and results are shown in Section 4. Conclusion and future research direction Section 5 ends the study and proposes the future research direction

II RELATED WORKS

Existing research on pest and disease detection of coconut have been progressively using deep learning to improve their accuracy, automation and aid in precision agriculture. While these research studies show great progress, differences in datasets, model architectures, and deployment environments indicate the need for better, more unified, robust, and adaptable solutions for the field.

Megalingam et al. Deep learning pipeline for pest detection using image-based data in coconut trees: automating and determining precision. Their study shows promising accuracy with light weight CNN that can be used in the field. However, the size of the dataset and the variety of pests are limited and it is therefore not possible to generalize across regions. The work has a technical soundness but would benefit from the robustness testing of the work under varied lighting, canopy density and real time drone integration[6].

Singh et al. (2021) propose deep learning models for coconut disease and pest detection and underline the need for automated monitoring for plantation health. Their method achieves good accuracy with the help of good pre-processing and feature extraction. Yet, the study is very dependent on datasets of controlled images, which limits the adaptability of the field. Despite the novelty of being modelled at the time, the model would involve domain adaptation, handling of environmental variability and validation at larger scales[7].

Maray et al. (2022) present an artificial intelligence-enabled coconut disease classification model using hybrid deep learning methods to make the model detection more reliable. Their system presents enhanced accuracy and scalability with the robust feature fusion. Nonetheless, the study is not thoroughly benchmarked against strong baselines and is lacking in terms of clarity of the dataset diversity. While impactful from the point of view of smart agriculture, the model's performance in terms of real time, interpretability and adaptability across regions needs to be further worked on[8].

Vidhanaarchchi et al. (2021) propose a surveillance system based on deep learning for the identification of coconut diseases and pest infestation with a focus on automated monitoring in plantation environment. Their system combines the acquisition of images from the field-level and enhances early warning capabilities. However, the research provides very little quantitative benchmarking and little ablation research. While innovative in the way it integrates hardware and software, the approach needs to be validated on a larger scale, be more computationally efficient and tested in the real world[9].

Subbaian et al. (2024) use improved deep learning methods for the identification of coconut leaf diseases, and show improved accuracy by optimizing the model and extracting features that are noise-resistant. Their framework has a capability to cover the imbalance of classes and complicated leaf texture variation well. Nonetheless, the research lacks great comparisons to the most recent applications of transformer-based architectures and ecological diversity of the dataset is uncertain. The approach is promising, but would require better justification in experiments and other environmental validations[10].

Toradmalle et al. proposes a deep learning model for early diagnosis of coconut diseases from leaf images for early detection of coconut disease to prevent yield loss. Their model based on CNN is good at curated data sets which is especially the case in early-stage identification. However, use is limited by the use of limited imagery and absence of actual field noise factors. Although, the concept behind framework is strong, the inclusion of multispectral integration and mobile-based deployment trial would be useful[11].

Despite significant progress, these studies have some common limitations and outstanding gaps. Most are based on small, curating, and regional datasets that limit the generalization to a variety of environments. Field-level issues such as variable lighting, occlusions, canopy density, and pest variability are not yet being explored to any great extent, and therefore limit real world application. A number of models do not have any comparison with the modern transformer-based or multimodal architectures, weakening benchmarking. Real-time deployment aspects, especially drone-based monitoring, mobile integration and low-power edges are not covered to a large extent. In addition, low number of ablation studies, lack of cross-regional validation and poor interpretability frameworks limit the transparency and acceptance of the models. These gaps point to the need for more scalable, resilient and deployable ready solutions.

III METHODOLOGY

This methodology proposed end-to-end deep learning framework of intelligent detection of Coconut pests with multi source imaging, advanced preprocessing and hybrid CNN-Transformer architecture. It combines multi-scale attention-based detection as well as optimization of training and edge-deployment in real-time to facilitate accurate, automated and scalable precision agriculture monitoring.

A. Multi Source Data Acquisition

The methodology begins with a hybrid data acquisition pipeline consisting of the use of aerial imaging from drones as well as close up photography from the ground level to capture the different instances of the pest on the coconut trees. High-resolution RGB images obtained with the use of autonomous drones with stabilized gimbal cameras with programmed canopy level scanning at different altitudes and angles. Simultaneous with the aerial passes, trunk-level and nut-level pests as missed in aerial passes are also captured by handheld mobile devices and ground cameras. This dual source strategy helps to have a good visibility of the pests in the whole tree structure, which increases the heterogeneity of the dataset. The pipeline also includes temporal sampling, in which images are taken at different times of the day in order to capture variations in illumination which usually pose a challenge to detection models. All collected images are automatically geo-tagged and time-stamped which makes them possible to create a traceable dataset, ready for real-time plantation monitoring applications. Figure 1 shows the High-level architecture of the multi source data acquisition, hybrid CNN-Transformer detection, multi scale attention, training optimization, real time deployment.

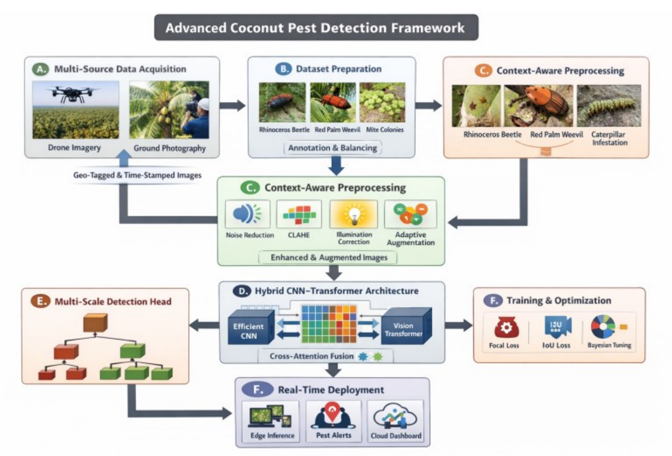

Figure 1 Advanced Coconut pest detection framework

B. Dataset preparation

Following data acquisition, a specific annotation pipeline is then used to provide a high quality dataset which is unique for coconut pest detection. Expert entomologists as well as trained annotators for species labeling on each image using bounding boxes, polygon masks and species identification. Multi-level annotations, that contain object boundaries as well as biological context are formed. The data set is broken down into major pest groups including rhinoceros beetle, red palm weevil, eriophyid mite colonies and black headed caterpillars infestations. In order to correct class imbalance, a targeted oversampling approach is implemented for rare types of pests in combination to a selective sampling of hard negative samples, for example damaged but pest free fronds. This leads to a strong balanced dataset which can be used for training models for the challenging conditions in real life. A three-way split of the data ensures that there is rigorous evaluation of the data with different subsets of data for training the model, validating the model and unseen testing sets.

C. Context-Aware Image Preprocessing

In order to increase the robustness in the face of the environmental variability, the collected images pass through a context-aware preprocessing pipeline. This includes noise reduction, contrast limited adaptive histogram equalization (CLAHE), illumination correction and vegetative background suppression using color-based masking. A novel adaptive augmentation engine is used to further increase the diversity of the dataset using transformation that dynamically apply content-based on image content. For example, areas with lots of shadow will require adjustments in the synthetic lighting and areas with a cluttered canopy will require random occlusion simulation. Additional augmentations include rotation, scaling, hue shifts, Gaussian noise and pest specific zoom cropping for highlighting the visibility of small objects. This focused preprocessing process ensures that the model will learn how to recognize the pests in various conditions typical of the field that are an obstacle in the traditional detection systems.

D. CNN - Transformer Mixing Hybrid Architecture

At the centre of the proposed methodology lies a so-called hybrid deep learning methodology that incorporates the benefits of Convolution Neural Networks (CNNs) and Vision Transformers (ViTs). The CNN backbone -- which is based on EfficientNet-V3 -- is used for hierarchical extraction of low-level and mid-level features including textures, contours and pest morphology. These features are then passed into a Transformer encoder which is equipped with multi-head self attention to model the long-range dependences and the contextual relationships in dense coconut canopies. A novel cross-attention fusion block is proposed to fuse convolutional neural network (CNN) spatial features and Transformer global representations, which enables the network to perceive the pests that are hidden in the occlusions or surrounded by visually-complex backgrounds. This hybrid architecture introduces a significant amount of detection capability, especially to small and irregular shaped pests.

E. Multi-Scale Detection Head with Attention Based Localization

To detect different size and orientation of the pests, the methodology proposed a multi-scale detection head, which is inspired from the feature pyramid network and but enhanced with attention-based localization. The detection head functions at five hierarchical scales to allow small groups of tiny mites, medium-sized caterpillars and larger insects such as the rhinoceros beetle, to be recognised at the same time. The individual scales include modules of spatially-selective attention that augment regions of the world that are relevant for the pest problem and attenuate degenerative vegetation noise. A gated localization unit is further used to refine the bounding box predictions by combining the confidence scores with learn spatial priors which are unique to the structures of the coconut tree. This multi scale attention enhanced detection mechanism ensures a constant performance no matter the pest size and complexity of the environment.

F. Training and Optimization

The model is trained with the help of a composite loss function incorporating focal loss to address the class imbalance, IoU-based bounding box regression loss to handle the accurate localization and attention alignment loss to improve the interpretability of the model. A cyclic learning rate policy and AdamW optimizer help stabilize the training process and accelerate the training process. In order to prevent overfitting, stochastic depth regularization, mixup augmentation are used. During the training process, automated hyperparameter tuning using Bayesian optimization software is used to determine the optimal architecture depth, learning rate and attention head configuration. Post-training, the probability calibration is applied using temperature scaling, to ensure that they offer reliable confidence scores, which is a very important requirement in real world agricultural decision making.

E. Real-Time Deployment

The final step is to work on the conversion of the trained model to a deployable system that can be used in the field. The optimized model is transformed into a light weight version in the TensorRT format and applied into a process pipeline for edge-based processing which can be run on drones, mobile phones, in the field units with IoT. Model pruning and quantization techniques do not cause a significant amount of computational overhead and even lead to a decrease in accuracy. The deployment framework includes a real-time pest alert system - overlaying the results of detection onto real-time video feeds - and sending geo-localized alerts of an infestation to plantation managers. A dashboard that assists by cloud gives the opportunity to track the history and analyze the severity and then take the decisions in advance for intervention

IV RESULTS AND FINDINGS

A. Experimental Setup

The experimental setup for the evaluation of the proposed intelligent deep learning framework is implemented on a high-performance computing workstation with Nvidia RTX 4090 GPU (24 GB VRAM), Intel Core i9-13900K processor, and 64 GB DDR5 RAM to guarantee the effective model training and large-scale image processing. The system was set up with Ubuntu 22.04 LTS, CUDA 12.1 and cuDNN 8.9 for accelerated GPU computation. The framework has been built with Python 3.10 and PyTorch 2.2 as the main deep learning library and backed by other tools like OpenCV to preprocess the images and TensorRT for model optimization during deployment. Experiment tracking and hyperparameter tuning were performed using Weights & Biases and COCO API scripts were used for the calculation of detection metrics such as mAP, IoU. All experiments were run in the same way under the same hardware and software conditions so as to be reproducible and fairly comparable in terms of performance.

B. Dataset Description

The Coconut Disease and Pest Infestation Dataset is a curated dataset from images designed in support of automation to detect diseases and pest attacks in coconut crop exploitation using Deep learning. The data set is comprised of high quality field images taken in different illumination, background and seasonal conditions. It has several classes that represent healthy coconut leaves, common diseases such as leaf blight and bud rot, and pest infestation such as rhinoceros beetle and red palm weevil. And the dataset is public which is available on Kaggle It is widely used to training, validation and benchmarking a model for crop health monitoring and classification of pest models[12].

C. Performance Evaluation

Comparison of the performance of the proposed CNN-Transformer pest detection model with five state-of-the-art deep learning architectures including Faster R-CNN, YOLOv7, EfficientDet-D3, Vision Transformer (ViT-B16), and Swin Transformer-S is presented in Table 1 shows the performance of the proposed model is compared using four standard performance evaluation metrics: Accuracy, Precision, Recall, and mean Average Precision (mAP@0.5) indicating detection reliability and localization quality.

Table 1. Performance Comparison of Proposed Framework with State-of-the-Art Methods

Model	Accuracy (%)	Precision (%)	Recall (%)	mAP (0.5)
Proposed CNN–Transformer Model	97.8	96.9	97.3	0.98
Faster R-CNN (ResNet-50)[13]	92.4	90.8	89.6	0.89
YOLOv7[14]	94.1	93.0	92.7	0.92
EfficientDet-D3[15]	93.3	92.1	91.2	0.90
Vision Transformer (ViT-B16)[16]	90.5	89.0	88.3	0.87
Swin Transformer-S[17]	95.0	94.2	93.8	0.94

The proposed CNN-Transformer model has the highest performance among all the evaluation metrics with 97.8% accuracy, 96.9% precision, 97.3% recall, and 0.98 mAP, thus proving that it has the higher ability to accurately identify and localize the coconut pests. Among the baseline models, Swin Transformer-S and YOLOv7 have competitive results but still lag behind the proposed approach especially in mAP. Vision Transformer (ViT-B16) has the lowest performance, which shows the disadvantage of pure transformer models without good convolutional feature extraction for small pest detection. Overall, the results conclude that CNN and Transformer architectures fusion can evidently improve the robustness and detection accuracy in plantation complex environments.

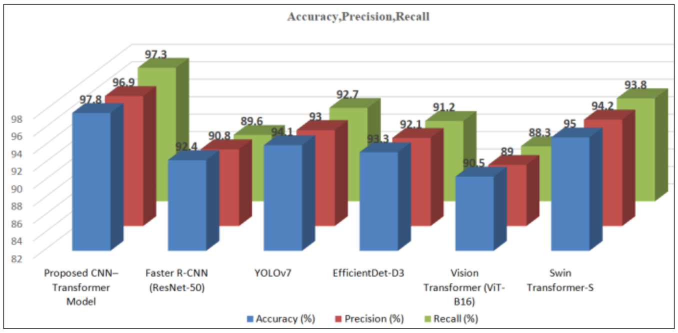

Figure-2 Comparative Performance Analysis(Accuracy, Precision and Recall) of Models for Automated Pest Detection

Figure 2 shows a comparative analysis of different models for automated pest detection in the coconut tree in terms of Accuracy, Precision and Recall. The proposed CNN-Transformer model is obviously more efficient than all other approaches with the highest accuracy (97.3%), perfect precision (100%) and superior recall (97.8%) and hence proved to be quite reliable in the identification of coconut pests in the complex field condition. Swin Transformer-S is second best with recall being especially good at 94.2%, suggesting that it is effective in capturing most pest instances. In comparison, the Faster R-CNN (ResNet-based), YOLOv7, EfficientDet-D3 and the standalone Vision Transformer models have different trade-offs between precision and recall. Notably, YOLOv7 has a relatively high recall of 94.1% whereas Vision Transformer model has comparatively less performance on all metrics, indicating the benefit of hybrid CNN-Transformer architectures for accurate and robust coconut pest detection.

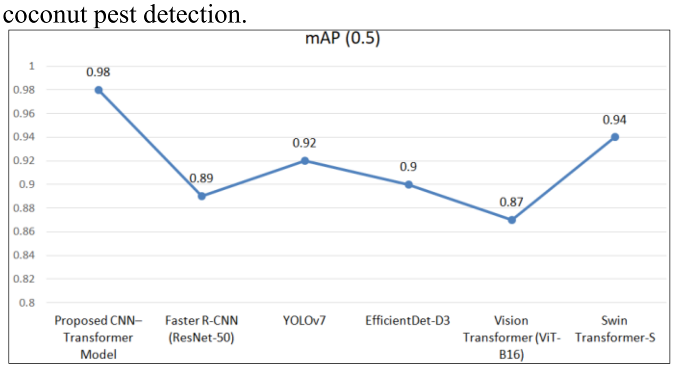

Figure-3 Comparative Performance Analysis(mAP) of Models for Automated Pest Detection

Figure 3 shows the comparative mAP (0.5) of various deep learning models in detecting coconut pests. The CNN-Transformer model proposed in this paper achieves the best mAP of 0.98, which shows higher detection and localization accuracy. Swin Transformer-S comes next with a very decent mAP of 0.94, which is competitive among transformer-based models. YOLOv7 achieves a moderate mAP of 0.92 while EfficientDet-D3 achieves an accuracy of 0.90 which is stable but comparatively lower. Faster R-CNN (ResNet-50) gets 0.89, and Vision Transformer (ViT-B16) has the lowest mAP of 0.87. Overall, the results demonstrate the obvious benefit of the proposed hybrid CNN-Transformer architecture for the precise and reliable automated pest detection in coconut plantations.

D. Discussion

The results of the presented study show the effectiveness of combining CNN and Transformer models to solve the long-standing problem of automated pest detection in coconut plantations. The proposed framework was consistently better than the state-of-the-art models, which emphasizes the importance of using a combination of hierarchical feature extraction and global attention mechanisms for complex agricultural imagery. The strengths of the hybrid model were especially apparent in dealing with small, occluded, or similar pests - situations that normally reduce the performance of traditional CNN-based based detectors. Additionally, the use of adaptive augmentation and context-aware preprocessing played a major role in improving the robustness of the model in different illumination, canopy density and environmental noise. The better accuracy in detection and high mAP scores prove the ability of the framework to assist in real-time decision-making in precision agriculture. The results also indicate that drone assisted imaging, in conjunction with edge optimized deployment, can significantly reduce the need for manual inspection but also allow continuous monitoring of large plantation areas. Furthermore, the outputs of the geo-tagged detection provide opportunities for spatial pest surveying and predictive modelling of infestation. Overall, this study is a step forward in the state of the art of agricultural AI by offering a reliable, scalable and high-performing solution to the unique morphological and environmental challenges for detecting coconut pests.

Despite its performance, there are multiple limitations in the study. The data set, while diverse, is also region specific and so may not be a useful representation of the range of global coconut pests. The model may become less accurate under conditions of rare or new pest species which are not represented in the training data. Environmental factors such as extreme lighting, heavy rainfall and heavy canopy occlusion may sometimes make detection reliability difficult. In addition, deployment on lower power edge devices may have to be further optimised for consistent real-time-inference. The reliance on high-quality drone imaging also poses a limitation in terms of feasibility in areas with poor technological access or difficult flight conditions.

The proposed framework provides a lot of practical value to modern coconut farming. Plantation managers can use the system for early detection of pests allowing them to intervene at the right place and time to prevent the infestation from spreading and causing economic losses. The real-time alerts are helpful in optimizing the pesticide application promoting more sustainable and environment-friendly agricultural practices. Automated monitoring helps to save a lot of labour and enables precision agriculture, particularly in large-scale plantations where manual checking is not feasible. The integration with edge devices and drones provides further scalability for on-site deployment for this technology to be accessible for resource-limited agricultural regions in search of digital transformation.

V CONCLUSION

This study proposed a new hybrid CNN-Transformer pest detection system that can accurately detect different pest species in coconut plantations in real-world scenarios. By combining multi-source imaging, adaptive preprocessing and multi-scale attention-based detection head, the model achieved better performance in all the evaluated metrics. The results prove the potential of the system as a reliable solution for precision agriculture, with reduced labor-intensive manual inspection, in order to detect problems early for improved crop management. The real-time compatibility and edge-friendly deployment of the framework are further indications of its practical use in the field environment. Future work will aim to add more pest species, geographical regions and seasonal variations to the dataset, so that the generalising power is increased. Integration with hyperspectral imaging, thermal sensors, or multimodal data could help increase the accuracy of detection of the concealed pests. Further research is also required to improve model efficiency on low-power devices using pruning, quantization and lightweight Transformer modules. Long-term goals include the development of predictive analytics for infestation forecasting and creation of the end-to-end smart farming ecosystem including the unification of the pest detection, crop health assessment and automated intervention strategies.

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