Harnessing the Power of Digital Technologies to Protect Plants & the Environment

D2.2: Report on SOTA in pest detection and prediction

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Executive Summary

The deliverable D4.2 within Work Package 2 (WP2) describes state-of-the-art (SOTA) in the field of pest and disease detection and prediction using digital technologies. It focuses on recent advancements and existing and novel methods that are relevant to the goals of the STELLA project.

STELLA Pest Surveillance System (PSS) is envisioned as a holistic digital system that will aid in the early warning and detection of regulated pests together with a response strategy by using modern sensing technology and Artificial Intelligence (AI). It will consist of three subsystems: 1) an early warning system using novel pest forecasting models and Internet of Things (IoT) sensors, 2) a pest detection system using remotely piloted aerial systems (RPAS), remote and proximal sensing as well as citizen science and traps, and 3) a pest response system providing geolocated hotspots for initiating containment and counteractive measures.

Section 1 highlights the challenges in food production related to crop damages caused by harmful diseases, quarantine and regulated non-quarantine pests (RNQPs), and the importance of early, automated pest monitoring systems. It also explains the importance of advanced technologies, including AI, machine learning, and remote sensing in improving pest detection and prediction to mitigate crop losses and environmental impacts.

Section 2 describes the role of T2.2 within WP2 in collecting, processing, and utilizing multi-source data.

Section 3 is the main part of this deliverable and consists of a literature review of recent studies, trends and technologies in pest and disease monitoring, detection and prediction. Based on comprehensive literature review, application of various digital technologies, data and machine learning techniques were identified and described. In addition, knowledge gaps, recent trends and potential future developments were identified.

This document has aim to reference and describe the key points of the relevant studies, that might be applied and optimized for the STELLA project. It also focuses on the limitations of current systems and research gaps, that STELLA aims to address.

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Glossary of terms and abbreviations used

List of Abbreviations and Acronyms	
AI	Artificial Intelligence
BPNN	Back-Propagation Neural Networks
CNN	Convolutional Neural Networks
IoT	Internet of Things
KNN	k-Nearest Neighbours
ML	Machine learning
NDVI	Normalized Difference Vegetation Index
PSS	Pest Surveillance System
RF	Random Forest
RNN	Recurrent Neural Networks
RNQP	Regulated non-quarantine pests
RPAS	Remotely Piloted Aerial Systems
SOTA	State-of-the-Art
SVM	Support Vector Machines
UAV	Unmanned Aerial Vehicle
UCP	Use Case Pilot
VI	Vegetation index
WP	Work Package
YOLO	You-Only-Look-Once

1. Introduction

Pests and diseases pose significant threats to agriculture and forestry, leading to substantial productivity losses and economic damage. Increase in population, climate change, intensified international trade are all trends that are increasing challenges in crop production and leading to severe crop damages caused by harmful diseases. To address the increasing food demands and risks in food production, it is critical to optimize the use of resources such as water and soil to enable high yield crops, and to decrease damages caused by pests.

One of the most harmful pests are quarantine and regulated non-quarantine pests (RNQPs), which are causing significant damages to crops. For instance, the Potato leafroll virus can lead to up to 50% yield losses (Garcia-Ruiz et al., 2021), while Grapevine Leafroll Disease can result in economic losses of around $40,000 per hectare[1]. Minimizing and managing RNQP outbreaks and preventing the introduction of quarantine pests are crucial step in protection of crop production. Despite the importance of pest detection and prediction, there is a significant lack of comprehensive monitoring and surveillance systems, particularly for quarantine pests and RNQPs.

Accurate knowledge of the location, extent, and severity of pest and disease occurrences is vital for guiding plant protection measures effectively (Zhang et al., 2019). In addition, early detection and monitoring are crucial factors for preventing disease spread, enabling effective management practices, and reducing both qualitative and quantitative crop yield losses.

Traditional methods of pest detection, such as visual inspections by experts, are both costly and time-consuming. These methods often only detect symptoms when they are visible, potentially delaying intervention. Molecular detection techniques have provided a more advanced approach, but the need for automated methods for crop monitoring and forecasting has become increasingly apparent. Systems that can perform automated and early pest detection on a large-scale tasks can play an important role in avoiding the excessive use of pesticides and chemicals, reducing both the damage caused to the environment and the production costs associated with the use of pesticides and chemicals (Kartikeyan & Shrivastava 2021).

The digitalization of agriculture, coupled with advancements in artificial intelligence, has revolutionized pest detection and prediction. Smart farming technologies now integrate remote sensing, image analysis, spectroscopy, Internet of Things, and multi-source data to support event forecasting, disease detection, and the efficient management of water and soil resources (Popescu et al. 2023). Pest detection and prediction technologies are significant in modern agriculture, offering vital tools for early identification and management of pest outbreaks. Early detection and monitoring are critical factors for preventing disease spread, undertaking effective management practices, and reducing both qualitative and quantitative crop yield losses.

Infrared, audio, and image-based sensors are used to identify pests, along with recent advances such as machine learning (Lima et al., 2020). Machine learning (ML) algorithms have enhanced the precision of pest detection (Mittal et al. 2024) through reliance on modern, technology-driven approaches. ML methods such as Support Vector Machines (SVM), Decision Trees, Random Forest (RF), k-Nearest Neighbors (KNN), and Naïve Bayes require substantial expertise and often struggle with complex backgrounds and varying lighting conditions (Guo et al., 2024). In contrast, deep learning algorithms, particularly Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Transformer networks, have emerged as more efficient and accurate solutions (Guo et al., 2024). These algorithms

[1] https://portal.ct.gov/-/media/caes/documents/publications/fact_sheets/plant_pathology_and_ecology/2019/leafroll_disease.pdf

can automatically learn complex feature representations from large datasets, improving their ability to generalize across diverse conditions and handle high-dimensional data. Neural networks enable machines to recognize patterns in data, representing a new trend in agriculture that enhances the detection and management of pests (Popescu et al. 2023).

A system capable of performing tasks of automated pest detection in the early phase of the development helps in the reduction of the use and risk of chemical pesticides and hazardous pesticides as part of the EC Farm to Fork and Biodiversity Strategies, targeting: 1) a 50% reduction in the use and risks of chemical pesticides and 2) a 50% reduction in the use of more hazardous pesticides. In addition, digital technologies enable farmers to identify pest species correctly and before disease cause significant damage which is important in reducing pesticide use, environmental damage, and production costs.

The integration of advanced technologies into pest detection and prediction offers a promising pathway to improving agricultural productivity while minimizing environmental impacts. By leveraging AI, machine learning, field sensors, traps, proximal and remote sensing, the agricultural sector can develop more precise, efficient, and sustainable pest management strategies, ultimately enhancing food security and reducing economic losses.

2. WP2 overview

The main task of T2.2 within WP2 is to collect, extract and pre-process all the proximal, IoT, trap (insect and spore) and remote sensing data that will feed T2.5 and WP3. Data collected in T2.2 will be used as inputs for training the pest detection models for the selected STELLA diseases. Developed AI models will be incorporated into STELLA PSS platform and evaluated in UCPs (Figure 1).

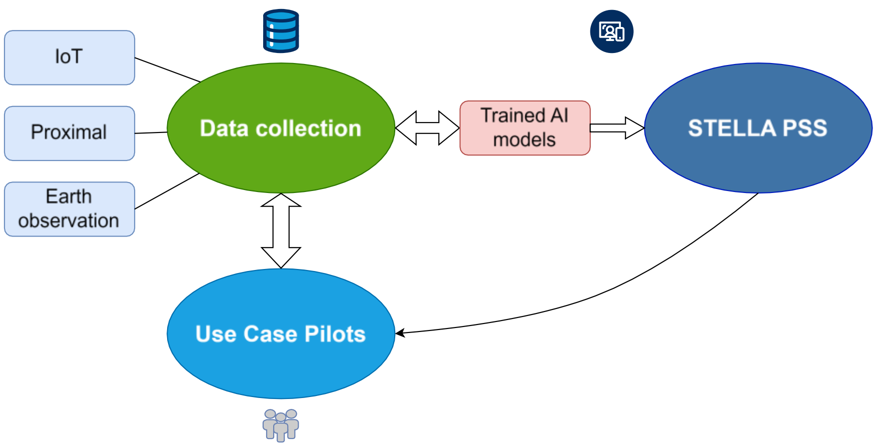

Figure 1 Interconnections between data collection and other project components.

For better understanding of current technologies for pest detection and prediction, this report aims to describe the current state-of-the-art (SOTA) in early warning systems and pest detection models, and to identify knowledge gaps. In addition, some of the described methods might be utilized in the context of STELLA project to improve the automation and efficiency of the STELLA pest detection and prediction tools.

3. Literature Review on Pest Detection

To identify recent advances and SOTA on digital tools used for pest detection and prediction with the focus on quarantine diseases, a literature review of pest detection and prediction tools was done. An overview of the latest research is presented by its comprehensive review of the literature. The focus of this review was on the use of digital technologies, data and machine learning techniques to identify studies and digital tools that are relevant for the goals of the STELLA project.

An extensive literature search was conducted using keywords: “pest OR disease detection”, “pest OR disease prediction”, “remote sensing”, “machine learning”, “deep learning”, “IoT”.

The literature associated with the keywords was identified in the following database and sources: Google Scholar, Science Direct and Scopus. Publications available from 2020 to 2024 were used for analysis, with certain additional relevant studies published before 2020.

In addition, Google’s search engine and AI search engines (Perplexity AI and Scopus AI) were used to collect information on the recent progress of the pest monitoring systems, and to identify platforms and apps used in pest monitoring in agriculture.

In total, 124 manuscripts were reviewed from peer-reviewed journals in English language. Reviewed manuscripts were used to describe the current trends in pest and disease detection and prediction in agriculture, to identify challenges and knowledge gaps, to categorize detection and prediction models per technology used, and to describe application of various ML techniques applied in recent studies.

Pest detection approaches

Several novel and non-invasive methods have been developed in the last decade which can be classified according to data used, such as:

- Image-based methods (Fuentes et al., 2017)
- Sensor-based methods (Navrozidis et al., 2023, Junges et al., 2020)
- Internet of things (IoT) (Passias et al., 2023)
- Hybrid data approaches (Dong et al., 2020)

The following table summarizes various pest detection methods, their descriptions, and references to relevant studies (Table 1). It also includes traditional and manual techniques.

Table 1 Overview of pest detection methods, their descriptions, and key references

Detection methods	Description	References
Visual inspection	Traditional method involving manual examination of crops by farmers or professionals.	Zhu et al., 2020 Hussain and Srikaanth (2024)
Molecular tests	DNA-based methods like PCR for identifying pest species from soil or plant samples.	Herbert et al., 2008
Proximal sensing and Image recognition	Employs deep learning algorithms (i.e., CNN, YOLO) and computer vision for identifying pests in images.	Chen et al., 2021
Remote sensing	Utilizes UAVs, satellites, and hyperspectral imaging to detect pest infestations over large areas.	Zheng et al., 2023
IoT	Integrates sensors and IoT devices for real-time monitoring and data collection on pest presence.	Chen et al., 2020 Passias et al., 2023
Hybrid approach	Integrates multiple data sources and leveraging various machine learning techniques	Yang et al., 2021

Image-Based Pest Recognition and Detection

Table 2 Summary of recently developed image-based pest recognition and detection methods

Method	Crop	Pest/Disease	Reference
Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD)	Tomato	9 tomato diseases	Fuentes et al., 2017
Faster R-CNN network	Tulip	Tulip Breaking Virus (TBV)	Polder et al., 2018
CNN using the GoogLeNet architecture	14 plant species	79 diseases (leaf damages)	Barbedo, 2019
Yolo V3	Tomato	Multiple tomato diseases	Liu and Wang, 2020
aster R-CNN	Dataset collected in field environment	Grasshopper identification	Yi et al., 2021
YOLO v4	Multiple crops	Mealybugs, Coccidae, and Diaspididae	Chen et al., 2021
Optimized Yolov3 ResNet50	Multiple crops	102 insect pests (IP102 dataset)	Prasath and Akila, 2023
Multi-scale Dense YOLO (MD-YOLO)	Apple orchards	Three lepidopteran pests	Tian et al., 2023
Faster-PestNet CNN	Multiple crops	IP102 dataset	Ali et al., 2023
YOLOv5 - involving the SWin Transformer, ResSPP, and C3TR	Various plants and pests	Dataset with 1309 images	Dai et al., 2023
Bayesian multi-task learning (using a ResNet18 backbone)	Corn, rape, rice, wheat	Aphids	Amrani et al., 2024
YOLO v8	Tomato	*Tuta absoluta*	Christakakis et al., 2024

Image-based pest recognition and detection involves using computer vision and ML techniques to identify and classify pests from images. Some of the recent studies that utilized images for identification of pests and diseases are presented in Table 2. Images used for ML techniques are collected by digital cameras or scanners. High-resolution cameras, including both RGB (Red, Green, Blue) and multispectral cameras, are commonly employed to capture detailed images of crops. These cameras can be mounted on various platforms such as drones, satellites, and ground-based vehicles, allowing for flexible and comprehensive monitoring of agricultural fields (Domingues et al., 2022). For more detailed and close-range imaging, ground-based systems are employed. These systems can employ handheld cameras and smartphones (Fuentes et al., 2017, Christakakis et al., 2024), mounted cameras on agricultural machinery or specialized robotic platforms (Cubero et al. 2020), stationary camera systems installed in fields for continuous monitoring (Preti et al. 2020, Tian et al., 2023). In addition, unmanned aerial vehicles (UAV) are used to offer the advantage of capturing images from different angles and heights, providing a more complete view of the crop conditions (Du et al., 2022). Moreover, advanced sensors such as hyperspectral sensors and thermal cameras are used to gather more specific data that can reveal information not visible to the naked eye, such as plant stress or early signs of pest infestation (Zhao et al., 2022, Singh et al., 2022, Bhakta et al., 2022).

Smartphones and cloud platforms have emerged as powerful tools for enabling farmers to detect pests in their crops more efficiently and effectively. This technology-driven approach combines the accessibility of mobile devices with the processing power and storage capabilities of cloud computing to create pest detection systems (Chen et al., 2021, Christakakis et al., 2024).

Machine learning methods

The field of image-based pest detection relies on various machine learning and computer vision techniques to process and analyse the collected images. Image-based methods utilize computer vision techniques, primarily using Convolutional Neural Networks (CNNs) (Popescu et al., 2023) and object detection models for pest and disease detection (Yi et al., 2021). These methods involve capturing images at various scales (leaf, canopy, field) and analysing them for signs of pests or damage.

CNNs are mainly and successfully used for the development of classification, object detection, or segmentation tasks in image analysis in pest detection as they are particularly well-suited to image recognition tasks (Chen et al., 2021, Popescu et al., 2023). The capability of neural networks to learn and recognize patterns in data have been utilized to detect insects and pests in crops. The CNN model typically consists of two main operators, which are the convolutional layer and the pooling layer. The convolutional layer can automatically extract more complex and significant features of the image. Due to the high computation of the convolutional network, the pooling layer reduces the number of parameters of the data. A large number the current research investigates the topic of pest image classification based on CNN models (Popescu et al., 2023, Mittal et al., 2024).

Advanced object detection architectures like Faster Region-Based CNN (Faster R-CNN) (Du et al., 2022), Single Shot Multibox Detecto (SSD) (Fuentes et al., 2017), and You Only Look Once (YOLO) (Dai et al., 2023) have significantly improved pest and disease identification and detection in crops.

Faster R-CNN is an object detection model with a two-stage learning method. In the first stage, it involves finding the region proposal and then it performs classification and bounding-box regression based on the region proposal in the second stage. Chen et al. (2021) used Faster R-CNN to detect pests by smartphone-based application and image recognition. Faster R-CNN F1 score accuracy in detecting mealybugs was 85%, 91% for Coccidae, and 83% for Diaspididae. The inference time of the model was 0.69 s per image. This study demonstrates the potential of combining deep learning object detection methods with mobile technology, aligning with a growing trend of developing smartphone applications that utilize deep learning models for on-site pest detection (eLocust3m[2], Plantix[3], Khan and Parihar, 2022).

Based on Faster R-CNN, Du et al. (2022) proposed **Pest R-CNN** for early detection and monitoring the occurrence of maize *Spodoptera frugiperda*, by using ortho-images acquired by an UAV flighting at a height of 1.5 m. It showed a better accuracy in comparison to R-CNN and YOLOv5 model showing its potential in utilizing low-cost remote sensing methods and applying them in actual agricultural pest detection. Authors proposed increasing the transferability by training the model on more images of leaves infested by different type of pests and in different geography zones. In addition, multi-source data approach (multi-spectral and hyper-spectral images) was proposed to further explore the combination of different remote sensing data by using this model.

[2] https://play.google.com/store/apps/details?id=plantvillage.locustsurvey
[3] https://plantix.net/en/

Another improvement of Faster R-CNN was proposed by Ali et al. (2023) by developing **Faster-PestNet**. It uses MobileNet as its base network and is tuned on the pest samples to recognize the crop pests of various categories. IP102 dataset (Wu et al., 2019) was utilized for model tuning and testing, which contains more than 75,000 in-field collected photos from 102 categories. Accuracy of 82.43% was achieved on the test set that contained several image distortions and images with complex background. In addition to pest recognition, it was proposed to evaluate the same technique for recognizing the crop diseases caused by pests.

With the development of object detection, **YOLO** series (Redmon et al., 2016) has been the industry-level standard for efficient object detection. It has also been widely used in the modern agricultural sector for real-time pest detection and monitoring (Popescu et al., 2023). YOLO uses a grid of cells to divide the image into multiple bounding boxes and predicts the object class and location for each cell. Dai et al. (2023) introduced improved YOLOv5m for pest detection improving robustness for recognizing plant pests and achieving better accuracy in comparison to previous versions. The latest YOLO versions that were employed for pest detection kept improving performances (enhancing precision and increasing detection speed) are YOLOv8 (Ye et al., 2024) and YOLOv9 (He et al., 2024).

The main advantages of YOLO in pest detection are its significant enhancement of detection accuracy and speed. For instance, the PestLite-YOLO model based on YOLOv5 improved the mean Average Precision (mAP) and provided real-time monitoring capabilities (Gao, 2024). Similarly, the SP-YOLO model based on YOLOv8n achieved higher precision and recall rates for soybean pest detection compared to traditional methods (Qin et al., 2024). Traditional machine learning methods require extensive preprocessing and feature extraction, which are time-consuming and less accurate compared to the end-to-end structure of YOLO models (Li et al., 2024b).

Datasets

The quality and diversity of training data significantly impacts the performance and generalizability of pest detection systems. There are several publicly available datasets and ongoing projects that provide data for pest detection and recognition in agriculture. For instance, datasets such as IP102 and PlantVillage have been extensively used to train models for detecting various pests across different crop types. IP102 is a large-scale pest dataset (Wu et al., 2019) containing 75,000 images from 102 pest categories. PlantVillage is another open access dataset (Hughes and Salathé, 2015) that includes images of healthy and diseased plant leaves, which can be useful for identifying pest damage symptoms. PlantDoc dataset includes 2,598 images taken in real-world settings across 13 plant species and 27 classes of diseases, contributing to improved accuracy of detection models (Singh et al., 2020).

For specific crop types or regions, custom datasets can often be built using a combination of field surveys, ground sensors, and collected images. Custom datasets allow for more precise and context-specific pest detection, as they can include images captured under local environmental conditions and feature pests that are prevalent in specific areas.

In the review of pest detection and recognition algorithms in agriculture by (Guo et al., 2024), authors confirmed the success of object-based deep learning algorithms for pest detection. It was stated that future work should focus on developing multimodal pest datasets, applying transfer learning, and designing hybrid architectures to address challenges such as background noise in complex agricultural environments and the diversity in pest appearance.

Limitation

While image-based pest detection algorithms demonstrated significant promise in pest detection, they face several challenges:

Imbalanced Class Distribution: Many detection systems struggle with extremely imbalanced class distributions, where some pest species are underrepresented in training datasets, leading to poor detection accuracy for those species (Lv et al., 2022). In addition, high visual similarity between different pest species can lead to misclassification, reducing the overall accuracy of detection systems (Liu et al., 2022, Ali et al., 2023).

Dataset size: Several authors highlighted the limitation related to small number of samples in public datasets for training the models for agricultural pest recognition (Barbedo, 2018, Barbedo, 2019, Zhao et al., 2022, Liu et al., 2022). Augmentation techniques were commonly used to artificially increase the number of samples for training (Barbedo, 2019, Patel and Bhat, 2021, Ye et al., 2022). Some widely used techniques in deep learning are: rotating images, flipping images, adding noise, cropping or zooming into specific parts of images. For instance, Barbedo (2019) proposed a method for increasing size and diversity of plant disease image datasets, where images of leaves were segmented into individual lesions and spots, which increased the sample size.

Complex Backgrounds: Field environments often have complex backgrounds, which can confuse detection models and lead to false positives or missed detections (Guo et al., 2024).

Small Pest Size: Detecting small pests is particularly challenging due to their tiny size and the need for high-resolution images to capture sufficient detail. (Liu and Wang, 2021, Khalid et al., 2023)

Real-Time Application: Many current systems are constrained to laboratory settings or controlled environments and struggle with real-time, in-field applications due to computational and logistical limitation (Liu and Chahl, 2018).

Trends and outlook

Recent trends in image-based pest detection systems emphasize advancements in machine learning, sensor technologies, and data fusion to improve pest identification and monitoring. Various models demonstrate high accuracy and speed, making them suitable for real-time field applications. Additionally, the integration of mobile and cloud-based platforms has made pest detection systems more accessible to farmers, allowing on-site identification through smartphone applications. Emerging methodologies incorporate multi-modal data fusion, combining image data with environmental factors like soil moisture and climate conditions, to provide a comprehensive understanding of pest dynamics.

While these technologies offer significant promise, challenges such as imbalanced datasets, complex field backgrounds, and the detection of small pests remain active areas of research, with future efforts focusing on hybrid models, improved datasets, and transfer learning to address these limitations.

The future of pest detection in agriculture relies on the development of high-quality image datasets and reliable detection models (Zhang et al., 2023). For example, hybrid models combining multiple algorithms can improve classification accuracy and efficiency (Divya and Santhi, 2023). Additionally, multi-modal data fusion, which integrates image data with other sensor inputs like infrared or audio, has the potential to further enhance detection capabilities (Lima et al., 2020, Dai et al., 2023). For example, Tian et al. (2023) plans to leverage the information on pest occurrence, as well as climate and soil moisture data, to establish a correlation between these factors and the presence of insect pests.

Developing automated systems for pest detection can reduce labour costs and increase accuracy. These systems can leverage machine vision and image processing techniques to selectively target pests and help in minimizing pesticide use (Kumar et al., 2017, Preti et al. 2020,).

Remote sensing methods in Pest and Disease Recognition and Detection

Remote sensing technology in pest management refers to the use of data collected at a distance from the plants, using satellites or drones, to detect changes in crop health that may indicate pest infestations. Remote sensing is able to detect plant damages and disease symptoms such as morphological changes outside the plant and physiological changes inside the plant (Zheng et al., 2023), providing noncontact and spatially continuous monitoring of diseases and pests efficiently. These symptoms are often reflected in the plant's spectral reflectance (Hall et al., 2016). Remote sensing tools can be used in diseases detection and monitoring in case a disease induce spectral response that can be detected by a specific sensor or sensors system (Zhang et al., 2019). This technology leverages the measurement of electromagnetic radiation reflected from crops to identify stress indicators caused by pests.

Therefore, based on the monitoring scale, remote sensing can be applied at leaf, canopy, field, and regional scale. Remote sensing systems are classified into groups that include: visible & near-infrared spectral sensors (VIS-NIR); fluorescence and thermal sensors; synthetic aperture radar (SAR) and light detection and ranging (Lidar) systems (Zhang et al., 2019). According to Zhang et al. (2019), types of plants' changes and symptoms caused by diseases or pests can be classified in the following categories: reduction of biomass, presence of lesions or pustules, destruction of pigment systems, wilting.

Table 3 Overview of recently developed remote sensing based methods and technologies used for pest and disease detection in crops across different platforms and sensors

Method	Platform/Sensor	Crop	Pest/Disease	Reference
Correlation analysis	UAV (hyperspectral and thermal)	Olives	*Verticillium* wilt	Calderón et al., 2013
Multilayer perceptron, CNN, RF, SVR	UAV (multispectral)	Potato	*Phytophthora infestans*	Duarte-Carvajalino et al., 2018
SVM and RF	ZY-3 satellite	Wheat	Wheat rust	Chen et al., 2018
Optimal threshold method	Sentinel-2	Wheat	Wheat Yellow Rust	Zheng et al., 2018
Various ML models	Ground-based hyperspectral sensor	Vineyards	Grapevine Leafroll-Associated Virus 1 and 3	Bendel et al., 2020
RF	PlanetScope satellite	Soybean	Sudden death syndrome	Raza et al., 2020
Image-based pest recognition	UAV and IoT	Rice	Multiple pests	Bhoi et al., 2021
Back-propagation NN and SVM	Multisource UAV	Arecanut	Yellow leaf disease	Lei et al., 2021
UNet++	Sentinel-2	Forest	Bark beetle and aspen leaf miner	Zhang et al., 2022
RF and XGBoost	UAV	Olives	*Verticillium dahlia* and other olive diseases	Navrozidis et al., 2023
Karhunen-Loeve Expansion (KLE)	UAV	Sugar Belle mandarin and avocado	Citrus canker and Laurel wilt disease	Hariharan et al., 2023

PLSR and linear regression	Hyperspectral satellite imagery (PRISMA)	Maize	*Helicoverpa armigera*	Sári-Barnácz et al., 2024

Recent advancements in pest detection leverage ML and remote sensing technologies to enhance efficiency and accuracy (Table 3). UAVs, satellites, and ground-based systems are commonly used for data collection. UAVs are particularly effective due to their high spatial resolution and flexibility (Jia et al., 2016, Ye et al., 2022, Ma et al., 2022, Yuan et al., 2023, Kouadio et al., 2023, Yu and Li, 2024). Techniques such as hyperspectral imaging and thermal imaging help in identifying specific pest-related stress by analysing the spectral signatures and thermal patterns of crops. For instance, thermal imaging can differentiate between healthy and infested plants based on temperature variations (Calderón et al., 2013). Spectral and hyperspectral imaging techniques can be used for detecting physiological changes in plants caused by pests, by identifying specific wavelengths and spectral indices that correlate with pest presence (Jones et al., 2010, Prabhakar et al., 2022, Deng et al., 2023).

High-resolution satellite imagery enables a monitoring of large agricultural regions. While these images may lack the precision for detailed pest and disease monitoring, they facilitate the quick detection of affected areas and the assessment of their spread (Zheng et al., 2018, Zheng et al., 2023).

Overall, integration of remote sensing and machine learning promotes resource conservation by enabling precise application of pesticides and fertilizers, reducing waste and environmental impact (Lobo et al., 2024, Wang et al., 2024a).

Machine learning methods

ML advancements have been utilized in pest detection models and in smart farming in general. ML models have been used to analyse data on diseases and relationship between the data (images, meteorological data, spectral reflectance) and disease occurrence and intensity (Zheng et al., 2021, Lei et al., 2021).

Various ML models, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Random Forests (RF), were employed for pest detection (Honkavaara et al., 2020, Du et al., 2022, Navrozidis et al., 2023). In addition, some more advanced models like multi-scale attention-UNet (MA-UNet) (Ye et al., 2022) and CNN-GAIL (Yu and Li, 2024) have shown superior performance in specific applications.

SVM algorithm was employed to predict the occurrence and severity of the yellow leaf disease of arecanut (Lei et al., 2021). This study used the UAV multisource remote sensing data and achieved classification accuracy of 86.30%, which was slightly higher than other classification algorithms (naïve Bayes, k-NN, decision tree). SVM algorithm demonstrated superior performance in another study (Calou et al., 2020) with 99.28% overall accuracy. In this study, high-resolution aerial images combined with machine learning algorithms have been utilized to monitor yellow sigatoka in banana crops. SVM was also applied to monitor wheat yellow rust based on Sentinel-2 multispectral images (Zheng et al., 2021). This model used two-stage vegetation indices (using images from two different days) and meteorological data achieving the classification accuracy of 84.2%.

RF is another traditional machine learning-based method used for pest detection as a binary classification model. Detection of incidence of the coffee berry necrosis was tested using Landsat 8 satellite imagery with RF classifier (Miranda et al., 2020). The authors suggested that integration with other remote sensing technologies would be beneficial for more precise detection as current overall accuracy of the detection was less than 0.6.

ML algorithms, RF and XGBoost, were used to classify olive trees as healthy or infected based on their spectral signatures obtained by UAV (Navrozidis et al., 2023). Use of these algorithms was evaluated and optimized by identification of the most important spectral features by Recursive Feature Elimination and Mutual Information techniques. The algorithms achieved high classification performance, with RF and XGB reaching roc-auc scores of 0.977 and 0.955, respectively. Both classifiers were trained with the initial dataset of 1507 features (11 statistics for 137 bands).

KNN algorithm is used for classification by finding the K nearest matches in training data followed by using the label of closest matches to predict. Traditionally, distance such as euclidean is used to find the closest match (Kartikeyan & Shrivastava 2021). KNN classifiers was employed using UAV-based multispectral imaging to detect *Cercospora* leaf spot in sugar beets, showing the highest accuracy compared to other classifiers (Tugrul et al., 2024).

Deep learning methods have emerged as particularly powerful tools with the ability to handle large, complex datasets. In addition, deep learning approaches have advantage of automatic feature extraction and have superior performance on image-based tasks. Several recent studies have successfully applied deep learning methods, particularly CNN models, in the detection of plant diseases and insects.

Du et al. (2022) proposed an end-to-end object-based deep learning model, **Pest R-CNN**, for detecting and localizing *Spodoptera frugiperda* infestations in maize using high-resolution UAV RGB images, achieving improved accuracy over Faster R-CNN and YOLOv5, and offering a promising approach for precision pest monitoring.

Zhang et al. (2022) combined the UNet++ architecture with an attention mechanism to detect bark beetle and aspen leaf miner infestations in British Columbia forests, achieving an accuracy of 85.11%, outperforming previous segmentation models. This deep learning-based method utilized Sentinel-2 multispectral data, vegetation indices, and RGB imagery for forest-pest damage segmentation, while the ResNeSt101 backbone and the scSE attention mechanism in the decoding phase improve segmentation results.

Data

Sentinel-2 offer 13 spectral bands of 10 to 60 m spatial resolution, and with two satellites cover the entire Earth every five days (Vuolo et al., 2016), providing data that can be utilized in pest detection. Sentinel-2 bands was also utilized by Zheng et al. (2018) by creating a new index, the Red Edge Disease Stress Index (REDSI), for detecting yellow rust disease of winter wheat. The optimal threshold method was used to assess REDSI's ability for mapping yellow rust infection resulting in the overall accuracy of 84.1% and 85.2% at the canopy and regional scale, respectively. The study concludes that Sentinel-2 MSI and the REDSI index can support effective disease detection.

Hyperspectral sensors, consisting of numerous narrow spectral bands, have the potential to detect diseases by capturing subtle changes in the spectral profile of plants that may be caused by pests and diseases. Potential of hyperspectral satellite imagery (PRISMA) was assessed in Sári-Barnácz et al. (2024) for monitoring maize ear damage caused by cotton bollworm larvae in Hungary, and compared to Sentinel-2, PRISMA performed better in grain maize and Sentinel-2 in sweet maize pest monitoring.

Ground-based hyperspectral imaging (400–2500 nm) was also tested to detect grapevine leafroll disease (GLD) caused by GLRaV-1 and GLRaV-3 in white and red grapevine cultivars (Bendel et al., 2020). Detection models successfully identified symptomatic, asymptomatic, and healthy plants in both greenhouse and field conditions.

High spatial resolution satellite data provide potential of more precise identification of individual infested plants and mapping of affected areas. For instance, **high spatial resolution ZY-3** satellite imagery was utilized to map wheat rust disease (Chen et al., 2018). By applying wrapper feature selection combined with SVM and RF classification methods, this study achieved high classification accuracy (90.80% to 95.10%).

Raza et al. (2020) investigated the use of another **high-resolution** (3m) **PlanetScope** satellite imagery combined with the random RF algorithm to detect sudden death syndrome (SDS) in soybean fields in Iowa, USA. The results showed that this approach can detect SDS-infected areas with over 75% accuracy, even before visible symptoms appear.

Lidar is an active sensor that can be integrated with other remote sensing data and used in prediction of disease and parasite outbreaks (Farhan et al., 2024). Franceschini et al. (2024) explored the use of LiDAR-derived point clouds and hyperspectral imagery to detect Blackleg disease in potatoes. Structural features from LiDAR were combined with vegetation indices derived from hyperspectral data, which increased the classification accuracy up to 18% compared to using vegetation indices as a single data source.

In addition, the potential of **thermal imaging** in the early detection of plant diseases and pests were confirmed by some studies (Singh et al., 2022, Hernanda et al., 2024). For example, severity of stripe rust disease in wheat was estimated using thermal images by Singh et al. (2022), showing similar or better estimates in comparison to visible images. Thermal imaging was used in combination with airborne hyperspectral images to distinguish between *Verticillium dahliae* and *Xylella fastidiosa* infections in olive trees (Poblete et al., 2021). Key spectral traits, such as the blue index, structural parameter, and carotenoid pigment content, were effective in differentiating *Verticillium dahliae* infections, while traits like the normalized PRI index, blue index, fluorescence curvature reflectance-based index, and chlorophyll index were crucial for identifying *Xylella fastidiosa* infections.

Multi-source reflectance data can improve the pest detection performance of models by providing diverse and complementary information (Li et al., 2024a, Yang et al., 2021). Multi-source data imagery (thermal, multispectral, and hyperspectral) was used to detect early-stage water stress caused by *Verticillium wilt* in olive trees (Calderón et al., 2013). Thermal indices like canopy temperature minus air temperature, Crop Water Stress Index, and physiological indices like chlorophyll fluorescence, blue/green/red ratios, and the Photochemical Reflectance Index were effective in identifying *Verticillium wilt* infection and assessing disease severity in olive orchards. Another study (Lei et al., 2021) used multispectral data and UAV high-resolution imagery to calculate five vegetation indices, including NDVI and OSAVI, and applied machine learning algorithms like back-propagation neural networks (BPNN) and SVM to quantify disease severity based on the yellowing area of areca crowns. Authors proposed integration of hyperspectral sensors with 3D laser radar and employing deep learning algorithms.

Spectroscopy

Spectroscopy is being used in agriculture for pest detection due to its ability to help identify plant stress caused by pests by analysing specific spectral signatures before visible symptoms appear (Mishra et al., 2024). Spectroscopy provides rapid, non-destructive methods to monitor and manage crop health (Crépon et al., 2023). It was used for early detection of infestation (Mishra et al., 2024), for monitoring and identification of pests (Hoseny et al., 2023), quality control (Johnson 2020), non-destructive analysis to identify wavelengths sensitive to specific diseases (Hoseny et al., 2023, Sawyer et al., 2023, Khan et al., 2021).

Sawyer et al. (2023) used RF based on hyperspectral images to identify Grapevine leafroll-associated viruses and grapevine red blotch viruses in a laboratory. Hyperspectral data within the visible range (from 510nm to 710nm) collected on leaf images (non-infected, infected by red blotch, infected by leafroll or co-infected by both) was utilized to train the RF model. When binarily classifying infected vs.

non-infected leaves, the RF model reached an overall maximum accuracy 82.8%, outperforming visual assessment of symptoms by experts when using RGB segmented images.

Zhang et al. (2020) also employed RF to test the detection of *Fusarium* head blight through the analysis of reflectance spectral data of healthy and diseased wheat ears by using 16 spectral indices. The severity of the disease (ratio of the diseased area) was predicted with R^2 value exceeding 0.90.

Another study (Hoseny et al., 2023), demonstrated the effectiveness of spectroradiometry and thermal imaging for non-invasive detection of spiny bollworm infestations in cotton bolls, identifying the Blue band and Normalized Pigment Chlorophyll Index (NPCI) as key indicators of pest presence. This study highlighted the importance of reducing pesticides through early detection of diseases.

Trends

Recent trends in remote sensing for pest and disease detection in crops have shown a clear progression towards increased spatial and spectral resolution, along with significant advancements in DL models. Traditionally, remote sensing studies have focused on detecting spectral variations caused by pest infestations or disease infections (Zhang et al., 2019). As those variations are often detectable only in specific and narrow wavelengths, shift toward multispectral and hyperspectral imaging is enabling more precise detection.

Satellites often cannot capture disease progression as precisely as hyperspectral sensors, and their spatial resolution is not high enough to detect small patterns in crops. UAV, on the other hand, can deliver highly detailed images, but their spatial range is limited and labour intensive, while frequent temporal observations are not always possible. This results often with a delayed detection response. To address the limitations of both, data fusion between satellite and UAV data have been used (Ye et al., 2022, Li et al., 2024a), which led to the improvements of the detection methods.

Thermal imaging is also gaining attention for its ability to capture early disease indicators. Another important trend is movement towards combination of multiple data sources. For example, the integration of multispectral, hyperspectral, and thermal sensors showed great promise for early-stage detection, though results often depend on the disease species (Calderón et al., 2013).

The integration of multi-source data, including meteorological data (Zheng et al., 2021), is becoming more common to predict favourable conditions for pest outbreaks and contribute to early detection.

While traditional machine learning methods like SVM and RF have yielded promising results, deep learning models, such as multi-scale attention UNet and CNNs, are beginning to outperform these approaches. Nonetheless, the manual annotation and preparation of training datasets is challenging, and lack of sufficient survey data is significant limitation for training the DL models.

Spectroscopy has emerged as a powerful tool, helping to identify key wavelength regions and develop predictive models for disease severity (Sawyer et al., 2023, Mishra et al., 2024). For instance, research on leaf scale using spectroscopy measurements were performed to develop detection and prediction models based on absorbance spectra, and some authors proposed further research to be applied on a large scale (canopy or field scale) (Dhau et al., 2017, Khan et al., 2021, Sawyer et al., 2023). However, not often these models have been upscaled.

Current studies largely focus on binary classification (healthy vs. infected plants), but advancements in disease severity quantification—such as pixel-level regression—are now exploring more granular data. Method of detection largely depend on pest species and regulations. In many cases, binary classification is sufficient because if a disease is detected, environmental regulations prescribe plants removal and there is no need to assess the disease severity (Picard et al., 2018).

Limitations

Detecting specific pests or diseases often requires identifying specific wavelengths, which varies by species and growth stage. This creates a need for more extensive research and validation, as one index or model cannot be generalized across different pests. A potential solution involves building simpler hyperspectral cameras that focus on the most informative wavelengths for detecting crop stress (Navrozidis et al., 2023). Transferability of models is also a challenge, as what works for one crop type or region may not apply universally (Bendel et al., 2020).

A key limitation is that many models and spectral signatures cannot reliably differentiate between diseases with similar spectral characteristics. This poses challenges for practical applications where multiple diseases share overlapping symptom profiles. Additionally, spectral characteristics can vary across different growth stages of the same disease, further complicating detection (Zhang et al., 2020). Models often require validation for each specific disease and growth stage to ensure accurate severity estimation. Timely detection of diseases is very challenging, because when remote sensing-based approaches identify a disease, it is usually too late to prevent the damages in the crops (Yang 2020).

Leveraging time series of satellite images, as in Zheng et al. (2021), gives an opportunity to capture disease progression patterns (Yang et al., 2018, Yu et al., 2022). Already mentioned data fusion of multiple data sources, such as UAV, satellites, ground-based sensors, and field observations, could be utilized by advanced DL models (Zhang et al., 2022) that can learn subtle spectral and spatial patterns of infestation. In addition, environmental conditions (soil humidity, soil nutrients, light intensity, meteoritical data) and historical disease patterns, give more contextual information to improve the accuracy of predictive models (Marković et al., 2021, Domingues et al., 2022).

For certain diseases, low spatial resolution remains to be the problem. Problem with mixed pixels (impact of shade, bare soil, other vegetation) often result in misclassification (Ma et al., 2019). To improve vegetation masking and excluding the impact of bare soil, some authors suggest obtaining surface elevation model with UAV or lidar to delineate rows of plants, or individual canopies (Weiss and Baret, 2017). Creation of 3D point clouds by LiDAR were utilized in agricultural and forestry applications in various studies (Wu et al., 2016, Xu et al., 2020, Lines et al., 2022). To address the mixed pixel issue, Fu et al. (2022) used derivative of ratio spectra (DRS) to help remove the interference of background elements in satellite multispectral image pixels, enhancing pest-related spectral features for Cotton aphid infestation monitoring. Another approach for unmixing in vineyards was proposed by De Petris et al. (2024), where Sentinel-2 NDVI data were integrated with high-resolution UAV-derived grapevine fraction cover maps. The UAV data enabled accurate separation of spectral contributions from grapevine rows and inter-rows.

Images collected at a 90° ortho-angle often do not give an opportunity to identify diseases occurring on lower layers of leaves or from the plant’s sides. To overcome this issue, Du et al. (2022) proposed capturing images from multiple angles in order to capture and infestation. Nie et al. (2024) successfully addressed this problem in detection of cotton *Verticillium Wilt* by UAV capturing images from multiple angles, in addition to satellite observations.

Future

While challenges remain, ongoing advancements in satellite technology, machine learning, and integrated pest management approaches continue to improve the ability to detect and differentiate crop diseases using remote sensing. Researchers propose higher-resolution sensors with more spectral bands, multi-date image capture, and improved multi-source data integration (Kouadio et al., 2023), including meteorological information, to enhance the early detection and prediction for pest outbreaks (Berger et al., 2022).

Transfer learning was proposed to address the issue of lack of datasets for training the models, which leverages pre-trained models applies them to new, but related tasks (Li et al., 2023). This is particularly important given the scarcity of large, annotated datasets in this domain. Additionally, self-supervised learning offers potential for future improvements, particularly for early monitoring and severity estimation.

Moreover, testing models on unknown areas and datasets is critical to ensure their robustness and applicability across diverse conditions (Bendel et al., 2020). Many models are trained on specific datasets and regions, but without validation in new contexts, their performance may degrade when applied to different crops, climates, or pest pressures.

IoT applications for real-time monitoring and data collection on pest presence

The Internet of Things (IoT) refers to a network of interconnected devices that can collect, share, and store information. In agriculture, IoT devices and weather stations are equipped with a variety of sensors for monitoring environmental conditions (soil humidity, soil nutrients, light intensity, meteoritical data), and pest activity (Sharma et al., 2020). It also offers farmers tools for early identification and targeted control of pests, which helps to improve pesticide spraying and fertilisation. IoT has the potential to significantly optimize agricultural yields and reduce resource consumption through the use of wireless sensors, UAVs, and cloud computing (Rehman et al., 2021). Despite initial costs, the long-term benefits of IoT, such as better plant monitoring, automated irrigation, weed control, and pest management, typically outweigh the expenses (Ndjuluwa et al., 2023). To explore the impact and applications of IoT in pest detection, several studies have demonstrated its effectiveness across various agricultural settings (Table 4).

Table 4 Overview of recent IoT based methods for pest and disease detection in agriculture

Method	Tools	Crop	Pest/Disease	Reference
YOLOv8	Smartphones, cloud computing and DSS	Tomato	*Tuta absoluta*	Christakakis et al., 2024
Optimized Yolov3 ResNet50	IoT sensors for capturing images	Multiple crops	102 insect pests (IP102 dataset)	Prasath and Akila, 2023
Multi-scale Dense YOLO	Insect traps, optical sensor	Orchards	Lepidoptera	Tian et al., 2023
SVM (IoT for activating spraying of pesticides)	Camera and NodeMCU	Multiple crops	Multiple diseases	Krishna et al., 2019
R-CNN and YOLOv5	Traps, cameras and mobile apps	Multiple crops	Whitefly pests	Cardoso et al., 2022
UNet and Deep batch normalized AlexNet	Web cameras and base station	14 species	38 diseases	Mishra et al., 2024
DMF-ResNet	Acoustic sensors	-	32 types of insects	Dhanaraj et al., 2023

Cardoso et al. (2022) presented an IoT network combined with computer vision techniques, using low-cost cameras and deep neural models like R-CNN and YOLO to autonomously detect and monitor Whitefly pests in traps, providing farmers with real-time data through a mobile app for more efficient, precise, and cost-effective pest management.

Another study that utilized captured plant leaf images by IoT nodes (Mishra et al., 2020), developed the sine cosine algorithm-based rider neural network (SCA-based RideNN) disease classification, which optimizes neural network weights for improved accuracy. In this study, algorithm detects a disease but not a specific type. In the later study (Mishra et al., 2024), PlantVillage dataset was utilized to train the models to identify first plant type, and disease type afterwards.

Krishna et al. (2019) employed SVM classification algorithm to detect various plant diseases utilizing a leaf image database. Upon disease identification, IoT system automatically triggers pesticide spraying using NodeMCU and sends an SMS alert to the farmer through a cloud platform.

IoT can also record insect noises (Dhanaraj et al., 2023) by deploying acoustic sensors connected to IoT networks, enabling autonomous pest detection by deep neural models.

Trends:

The integration of IoT in agriculture has been expanding recently and increasingly used to monitor environmental conditions and pest activity remotely, providing farmers with continuous, real-time data. It helps to reduce human intervention through automation and enables farmers to constantly monitor their farms.

IoT systems has evolved from monitoring tools to detection systems utilizing ML and DL models. They use web cameras to take images of plants which are then preprocessed and analysed by ML algorithms for pest and disease identification. In addition, IoT collects various environmental data (i.e., soil moisture, vegetation cover, precipitation, temperature) which are important for agriculture and are used as features in pest modelling.

Advancements in cloud computing performances and its incorporation into IoT solutions, allowed large data processing and storage, which supports real-time analytics for better decision-making. In addition, costs in IoT sector have been decreasing, making the technology more accessible. This trend contributed to the development of the pest management systems and utilization of mobile applications, enabling real-time pest and disease detection and data-driven decision-making.

Limitations:

While IoT brings several advantages to pest detection, certain limitation exists. Setting up IoT systems requires specialized infrastructure and expertise, making it difficult for smaller farms to adopt. Even though long-term benefits often outweigh initial costs, high expenses can be an obstacle for small-scale farmers. The absence of uniform standards across IoT platforms and devices can lead to compatibility issues, hindering the integration of different systems (Kiobia et al., 2023).

In addition, accuracy of the models may be lower due to low-quality images or insufficient training datasets, especially across early pest developmental stages. This can result in false positives/negatives classification. Some current systems are only capable of detecting whether a plant is affected by a disease but not the specific type, limiting their practical applications.

Accuracy problems can be addressed by large and annotated datasets collected throughout different development stages and under real conditions. Combination of computer vision with other data sources, such as acoustic or thermal sensors, have proved to improve detection accuracy (Poblete et al., 2021, Dhanaraj et al., 2023).

Future

Integration of IoT pest monitoring systems with precision spraying or robotic pest removal mechanisms would have a potential for real-time, automated pest control (Wang et al., 2024b). Also, interconnected pest monitoring networks could help predict and manage pest outbreaks on a larger scale by analysing global data.

With the constant improvement of AI and DL, future systems may enhance disease classification using more sophisticated neural networks trained on large datasets. The creation of extensive image datasets under real-world conditions will enhance the accuracy of pest detection systems and improve models' robustness across different environmental scenarios.

Multi Data Approaches

Using data from multiple sources for pest detection in agriculture involves integrating various types of information offering several advantages over traditional single-source methods. Combining diverse data types such as imagery, remote sensing, climatic conditions, and soil attributes can significantly improve the accuracy of pest detection models (Li et al., 2023, Huang et al., 2022, Zheng et al., 2021).

Qi et al. (2024) developed a monthly habitat suitability monitoring model for fall armyworm in Africa using multi-source earth observation data, including climate, land use, vegetation (NDVI), and soil variables. By integrating exploratory factor analysis and the RF algorithm, the model achieved high performance metrics (AUC > 0.9)

Gao et al. (2020a) integrated IoT and UAVs for monitoring crop diseases and pests, combining weather data from IoT sensor nodes with spectral image analysis from UAVs. The framework demonstrated how temperature and rainfall influence wheat disease occurrence, enhancing agricultural monitoring and decision-making.

Zhang et al. (2018) presented a vegetable pest early warning system based on multi-dimensional big data by using a multi-sensor network to collect data on pests, soil, environment, eco-climate, weather, and the images of pests, and applying machine learning algorithms such as Back Propagation Neural Network. This multi-sensor network system showed that actual environmental data contribute to the accuracy of the pest prediction model.

Huang et al. (2022) proposed combining mobile internet survey data and high-resolution spatial-temporal meteorological information to address the limitations in pest forecasting models of Alternaria leaf spot disease in apple caused by insufficient availability of the disease in the affected region. Temperature and humidity during key periods were identified as sensitive inputs for the model.

Bhoi et al. (2021) proposed an IoT assisted UAV based pest detection model to identify the pests in the rice during its production in the field. AI was employed to send images captured by UAV to the Imagga cloud[4], where pest identification is carried out and the user is informed.

Approach by Zheng et al. (2021) showed potential for regional-scale disease monitoring by model combining Sentinel-2 multispectral vegetation indices with meteorological data in wheat yellow rust monitoring.

Transfer learning using multi-source data has shown promising results for pest detection (Li et al., 2023, Devi et al., 2023, Guo et al., 2024). This approach is particularly useful in agriculture, where collecting labelled data for pest detection across diverse environments can be challenging. By using models pre-trained on large, generic datasets, transfer learning allows to fine-tune models on specific agricultural pest data, incorporating multi-source inputs for more accurate detection (Li et al., 2023).

Pest Detection Platforms

Pest detection platforms have become increasingly sophisticated and essential in modern agriculture, and with the technological improvements they support pest control practices (Theodorou et al., 2023). In addition, mobile applications make pest management more accessible, particularly for small-scale farmers who may not have access to advanced technologies. To address a limited pool computing

[4] https://imagga.com/

capabilities of smartphones, implementation of a cloud platform with a web interface and smartphone app is often employed (Chen et al., 2021) to perform the pest detection in real time.

Several platforms and mobile applications are available for pest detection and management in agriculture, many of which use AI, remote sensing, and data integration to help farmers monitor and control pest outbreaks (Table 5).

Table 5 Overview of commercial platforms and digital systems for pest and disease monitoring in agriculture

System	Technology used	Data inputs	Plant type	Reference/link
VELOS	IoT, UAV, UGV	Weather patterns, soil conditions, and pest populations	bean cultivations	https://users.uowm.gr/louta/CONFERENCES/C71.pdf
Plantix	Phone app	Image based recognition and treatment	30 crops, 120 plant diseases	https://plantix.net/en/
Agrio	Phone app	Forecast and detection		https://agrio.app/
CropDiagnosis app	Phone app – user inputs	Questionnaire for symptoms		https://www.cropdiagnosis.com/portal/crops/en/home
Croptimus platform	Scouting system, cameras	Image based recognition		https://www.fermata.tech/#technology
iFarmer			Sugarcane	https://ifarmer.asia/

Systems like **VELOS** utilize remote sensing and sensor technologies to collect high-quality data, which is then used to monitor crop development, detect pests, and assess pest management strategies. It analyses data on weather patterns, soil conditions, and pest populations to help in making informed decisions on pesticide application and other pest control measures (Theodorou et al., 2023).

Plantix[5] is an android-based farming assistant tool that provides crop health information, helping with identification of plant diseases using computer vision and deep learning techniques. Its database contains half a million pictures covering 30 crops worldwide and offers remedies for over 120 crop diseases. Users can take a photo of an affected plant and receive an automated diagnosis of the problem (Samai et al., 2023).

Agrio[6] is another mobile application that uses AI to identify plant diseases, pests, and nutrient deficiencies and provides treatment recommendations using on image-based disease recognition. It also gives warning notification about the potential of spread of diseases based on satellite images and weather models (Khan and Parihar, 2022).

A smartphone application **eLocust3M**[7] for real-time tracking and reporting of locust swarms is using data collected by crowdsourcing activities. Tabar et al. (2021) integrated this data with additional

[5] https://plantix.net/en/
[6] https://agrio.app/
[7] https://www.fao.org/locust-watch/activities/innovation/digital-tools/en

remote-sensed environmental data (i.e., soil moisture, vegetation cover, precipitation) using neural network architecture to provide accurate predictions of locust movement in East Africa.

Early Detection and Prediction

Importance of early detection of plant pathogens is crucial for minimizing the risk of disease spreading, crop damage and economic losses by enabling timely interventions. Early detection refers to the identification of pests or diseases at their initial stages, often before they reach damaging levels. This approach focuses on recognizing signs of infestation or disease early enough to implement management strategies that can effectively mitigate their impact.

Pest prediction involves forecasting future pest populations and potential outbreaks based on current data and historical trends. It uses models that integrate various factors, such as environmental conditions, pest life cycles, and past infestation records, to estimate the likelihood of pest issues arising (Marković et al., 2021, Domingues et al., 2022).

Early detection allows for timely management practices, reducing the spread and impact of diseases and pests on crops, which is essential for maintaining crop health and productivity (Martinelli et al., 2015, Buja et al., 2021, Zhang et al., 2024). By identifying issues early, farmers can apply targeted treatments, reducing the unnecessary use of pesticides (Soares et al., 2022). This not only lowers costs but also minimizes environmental pollution (Martinelli et al., 2015, Hoseny et al., 2023). In addition, early warning systems reduce the labour and expertise required for disease monitoring, making it a cost-effective solution for large-scale farming operations (Long, 2023).

There were several studies and products that explored possibility of early detection of diseases. Arapostathi et al. (2024) employed UAV-based multispectral remote sensing to detect early symptoms of peach flatheaded root borer infestation in orchards, using vegetation indices and tree crown area data. The XGBoost model proved to be the most effective, achieving an accuracy of 0.85, with marginal variations from the other tested ML models, utilizing UAV-derived multispectral data where NDVI was the most critical predictor of infestation.

Ye et al. (2022) proposed a UAV-based multi-scale attention-UNet model to address the limitations of traditional multi-phase satellite-based methods for detecting pine wilt disease. This model improved pest detection using monophasic aerial imagery and data augmentation techniques, allowing for earlier and more accurate prediction of pest infestations.

Marković et al. (2021) proposed a ML model to predict daily pest occurrences, focusing on *Helicoverpa armigera*, by analysing air temperature and relative humidity. Extending the prediction window to five days improved accuracy from 76.5% to 86.3%, reducing false detections. This validated the effectiveness of using longer periods for better pest occurrence prediction.

David et al. (2023) also highlighted the critical role of weather data in predicting crop disease and pest outbreaks. In their study, weather conditions, such as temperature, humidity, and rainfall, proved to be key accelerators for the spread of diseases and pests.

Artificial inoculation is method sometimes used in research to provide data for training machine learning models for early detection (Chivasa et al., 2021, Duan et al., 2024). Soares et al., 2022 inoculated coffee seedlings with *Hemileia vastatrix*, causing coffee leaf rust, to train SVM and ANN models on labelled dataset. Multispectral images were collected using UAV in different intervals after the inoculation to analyse spectral curves of healthy and infected plants, and detection accuracy was 80% at an asymptomatic stage (15 days after inoculation).

Trends, limitation, future

The importance of early detection lies in identifying pests and diseases before they reach destructive levels, enabling timely interventions. Early detection has been becoming increasingly important in reducing crop damage, economic losses and environmental harm, because simply detecting a disease in later phase might be too late for protecting a crop. Recent trends in this area involve the integration of various technologies and approaches to enhance the accuracy and effectiveness of detection and prediction systems.

To timely detect or predict the development of a disease, many studies are moving towards the integration of multiple data sources. Collecting various parameters that affect the appearance of pests are used as an integral part of early detection models. However, models are trained only for specific pest and input features depend on the studied pests (Marković et al., 2021). It leads to lack of flexibility of models and inability to employ them onto different pest species.

Exploration of various models have been common to utilize the increasing availability of data sources (metrological data, UAV, satellite, traps, field sensors). Future ML models will likely incorporate transfer learning and ensemble approaches, enabling them to generalize better across different crops and pests.

IoT devices and sensors are also being used to provide real-time data on environmental conditions and pest activity, further enhancing early detection systems. Utilization and availability of mobile apps by farmers leads to development of mobile platform and systems that help in obtaining real-time data useful for decisions such as targeted treatments and pesticide use (Domingues et al., 2022, Arapostathi et al., 2024).

One of the most significant trends is the use of UAVs equipped with multispectral or hyperspectral sensors. These UAVs capture high-resolution images of crops, allowing early detection of subtle symptoms that may not be visible to the naked eye (Ye et al., 2022).

As in the models that aim to detect the presence of pests or occurrence of diseases, early detection models largely depend on data reliability and their complexity and dependency on specific datasets, which limits their generalizability. Furthermore, the expertise required to manage and interpret the data from these systems, and knowledge about the early development of specific pests, remains a barrier to wider adoption.

As costs are decreasing and technology advances, it is expected to build up on existing DL models. Moreover, with the increase of pest monitoring networks on larger scales, a broader understanding of pest movement and outbreaks could be achieved.

Discussion and Conclusion

Based on the 8 selected pests present in all 6 UCP region (6 RNQP, 2 Quarantine), STELLA aims to develop models to detect these pests using data obtained by available technologies (IoT, remote and proximal sensing), and to contribute to early warning systems in preventing spread of diseases caused by selected pests. Table 6 summarizes recent studies that have explored and developed methods for detecting pests and diseases aligned with STELLA's objectives. These studies employ technologies and analytical methods for diverse crops, offering valuable insights for advancing pest detection systems. While some studies directly address pests and diseases relevant to the STELLA project, others focus on similar challenges or pathogens to provide additional insights into applicable methods and technologies.

Table 6 Overview of recent studies utilizing various technologies and methods for detecting pests and diseases in crops relevant to the STELLA project.

Crop	Pest/Diseases	Technology	Method	Reference
Olives	*Verticillium* wilt	UAV (hyperspectral and thermal)	Correlation analysis	Calderón et al., 2013
	Verticillium dahliae and *Xylella fastidiosa*	UAV (hyperspectral and thermal)	RF	Poblete et al., 2021
	Verticillium dahlia	UAV	RF and XGBoost	Navrozidis et al., 2023
Tomato	*Ralstonia solanacearum*	RGB images	CNN	Vásconez et al., 2024
	Ralstonia solanacearum	Spectrometry	PCA and SVM	Cen et al., 2022
	9 tomato disease	Image-based	Faster R-CNN, Region-based Fully CNN (R-FCN), and Single Shot Multibox Detector (SSD)	Fuentes et al., 2017
	Multiple tomato diseases	Image-based	Yolo V3	Liu and Wang, 2020
	Tuta absoluta	Image-based	YOLO v8	Christakakis et al., 2024
Vineyard	GLRaV–3	Spectrometry	PLSR, SMLR to analyse key wavelengths; Quadratic Discriminant Analysis (QDA) and Naïve Bayes (NB) classification	Sinha et al., 2019
	GLRaV–3	Ground-based hyperspectral sensor	Various ML models	Bendel et al., 2020
	GLRaV–3	Spectrometry	ANOVA and linear regression for sensitivity analysis; LS-SVM classifier	Gao et al., 2020b
	GLRaV–3 and grapevine red blotch virus (GRBV)	Spectrometry	CNN and RF	Sawyer et al., 2023
	GLRaV–3	UAV	GLDCNet	Liu et al., 2024

	Grapevine yellows	WorldView-2 satellites	SVM	Zibrat and Knapic, 2024
Potato	Vascular wilt - *Verticillium* spp	UAV	RF	León-Rueda et al., 2021
	Alternaria solani - early blight	UAV	U-Net	Vijver et al., 2022
Apple	Apple fire blight - *Erwinia amylovora*	UAV	RF and SVM	Xiao et al., 2022

This review on the latest developments in the application of digital tools for pest detection and prediction showed significant progress in recent years and growing utilization of ML and DL techniques in agriculture monitoring. By combining diverse data types, researchers can develop more comprehensive models that account for various factors influencing pest dynamics.

A lot of studies focused on image-based methods. CNNs and object detection models like Faster R-CNN, YOLO, and SSD have demonstrated high accuracy in identifying pests from images. In recent years, UAV-based imagery has become valuable for disease monitoring at field and farm scales, driven by decreasing costs of equipment, the need for effective solutions for managing plan diseases, and advancements in processing capabilities. Satellite data is increasingly being used for large-scale and continuous pest monitoring. However, its spatial resolution is not always sufficient for early recognition of small-scale changes in crop health.

The development of mobile applications and cloud platforms has made pest detection systems more accessible to farmers, enabling on-site identification and real-time monitoring through smartphones. IoT systems has also evolved, and devices and weather stations equipped with a variety of sensors for monitoring environmental conditions offer tools for early pest detection. By integrating IoT technology with cloud computing, mobile applications are widely used to assist farmers in monitoring pests (Ndjuluwa et al., 2023).

Authors frequently suggested multi-source data approach to address limitations of individual data sources. Notably, there is an evident trend of combining data from various sources, such as imagery, remote sensing, climatic conditions, and soil attributes. Factors such as advanced DL techniques, large-scale datasets, improved computational power and affordability of sensors, contribute to the increase of research on multi-source data integration for pest detection. By utilizing various data, a more holistic view of pest dynamics is possible, as well as capturing diverse factors influencing pest outbreaks (i.e., microclimatic variations, soil conditions, vegetation structure). Different data sources can complement each other in terms of temporal and spatial resolution. For instance, satellites provide frequent but coarse observations, while UAVs offer high-resolution imagery over smaller areas.

Practical applications are becoming widely used due to development of platforms and mobile applications that are available for pest detection in agriculture. However, there is still a need for more complex and extensive datasets that would enable efficient training of models capable of addressing various challenges, such as background noise, complex environments, transferability across regions, and visual similarities between different pest species. The availability of open-source, freely accessible data on pest outbreaks through online repositories obtained by ongoing projects and collaborations, would significantly contribute to the accuracy and generalizability of pest detecting systems and their practical applications in real-world agricultural settings.

Based on multiple studies in the field of pest monitoring, authors generally agree on the effectiveness of ML and DL techniques in improving pest detection accuracy. There is also consensus on the benefits of integrating remote sensing and IoT technologies for real-time monitoring and data collection, and importance of multi-source data fusion.

Need for larger and more balanced datasets, that are open-source and can be used to train models for identifying multiple diseases, was highlighted in many studies and literature reviews. However, while some authors use or suggest transfer learning and data augmentation techniques to address this issue (Barbedo, 2019, Patel and Bhat, 2021, Ye et al., 2022, Li et al., 2023), others advocate more extensive data collection (Wu et al., 2019, Zhang et al., 2023).

Future directions in the field of disease management in agriculture are expected to emphasize the development of more advanced DL algorithms, high-quality datasets (Zhang et al., 2023), additional expansion of hybrid models (Divya and Santhi, 2023), development of methods for real-time data analysis and decision-making tools (Domingues et al., 2022, Arapostathi et al., 2024), efforts to reduce labour costs and integrating AI and IoT (Sharma et al., 2024).

In conclusion, the integration of digital tools, machine learning, and remote sensing technologies has significantly advanced the field of pest detection and prediction in agriculture. Proximal and image-based methods, remote sensing, and IoT integration have proven to be effective in providing accurate disease detection and pest identification, which is essential for effective pest management. The use of multi-source data and emerging trends such as transfer learning and hybrid models offer promising tools for further improving pest detection systems. However, challenges such as imbalanced datasets, complex field backgrounds, and the need for high-resolution images remain. Future research should focus on addressing these challenges and developing more robust models. The practical applications of these technologies, including mobile apps and platforms for farmers, highlight their potential to revolutionize pest management practices and improve agricultural productivity.

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