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VIEWPOINT

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Can artificial intelligence be integrated into pest monitoring schemes to help achieve sustainable agriculture? An entomological, management and computational perspective

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Abstract

1. Recent years have seen significant advances in artificial intelligence (AI) technology. This advancement has enabled the development of decision support systems that support farmers with herbivorous pest identification and pest monitoring.
2. In these systems, the AI supports farmers through the detection, classification and quantification of herbivorous pests. However, many of the systems under development fall short of meeting the demands of the end user, with these shortfalls acting as obstacles that impede the integration of these systems into integrated pest management (IPM) practices.
3. There are four common obstacles that restrict the uptake of these AI-driven decision support systems. Namely: AI technology effectiveness, functionality under field conditions, the level of computational expertise and power required to use and run the system and system mobility.
4. We propose four criteria that AI-driven systems need to meet in order to overcome these challenges: (i) The system should be based on effective and efficient AI; (ii) The system should be adaptable and capable of handling 'real-world' image data collected from the field; (iii) Systems should be user-friendly, device-driven and low-cost; (iv) Systems should be mobile and deployable under multiple weather and climate conditions.
5. Systems that meet these criteria are likely to represent innovative and transformative systems that successfully integrate AI technology with IPM principles into tools that can support farmers.

KEYWORDS

artificial intelligence, decision support system, image recognition, integrated pest management, machine learning, pest management

INTRODUCTION

Infestation with herbivorous pests can be extremely damaging to crop production (Culliney, 2014), with approximately 20%–30% crop losses caused by herbivorous pests and pathogens worldwide (Savary et al., 2019). Herbivorous pest infestations are also anticipated to increase under a changing climate (Deutsch et al., 2018). Farmers often use plant protective products, such as pesticides, to manage herbivorous pest infestations. However, there are increasing environmental, ecological and public concerns around the use of pesticides, a growing need to use pesticides in a more environmentally conscious manner, a requirement to reduce overall pesticide use and a drive to promote uptake of alternative management options. Restricting pesticide use is also important in order to reduce the likelihood that pesticide resistant populations will develop (Bass et al., 2015).

Integrated pest management (IPM) aims to reduce reliance on plant protection products through the implementation of multiple pest management techniques. There are eight key IPM principles that underpin this (Barzman et al., 2015):

1. Prevention and suppression
2. Pest identification and monitoring
3. Decision based on monitoring and thresholds
4. Non-chemical methods
5. Pesticide selection
6. Reduced pesticide use
7. Anti-resistance strategies
8. Evaluation

In general, these principles provide a logical, stepwise process to assist growers with their decision-making. Recently, a more holistic system, Agroecological Crop Protection, has been suggested as an alternative to IPM (Deguine et al., 2021). The underlying principles and aims of IPM and Agroecological Crop Protection are similar, however, Agroecological Crop Protection places greater emphasis on holistic and sustainable farming within an ecosystem context, whereas IPM has become synonymous with pest and disease management (Deguine et al., 2021). Nonetheless, a key element in both schemes is the correct identification and sustained monitoring of herbivorous pests and the integration of the information gained from these monitoring efforts into crop protection practices. Correct identification of the pests present in agricultural fields, and the combination of this with appropriate management advice, is essential if agricultural pests are to be controlled successfully (Ellis et al., 2014; Ramsden et al., 2017).

CORRECT PEST IDENTIFICATION AND SUSTAINED HERBIVOROUS PEST MONITORING: KEY CHALLENGES FOR FARMERS

The correct identification of herbivorous pests is a key challenge for most farmers and advisors. Farmers need to be able to confidently identify herbivorous pests, and/or the damage caused by these pests, in order to apply correct and timely pest management interventions. The sustained monitoring of herbivorous pest populations, particularly the build-up of pest populations, is also an important component that underpins IPM and Agroecological Crop Protection principles (Barzman et al., 2015; Deguine et al., 2021). Generally, most farmers follow established economic thresholds (Ramsden et al., 2017). Economic thresholds (hereafter, thresholds) are the number of herbivorous pests per plant, or unit area, above which there is sufficient risk that the level of crop damage caused will result in economic yield loss (Higley & Pedigo, 1993; Pedigo et al., 1986). Farmers primarily apply pesticides, or other interventions, once herbivorous pest populations within the crop breach these thresholds. Therefore, the sustained and frequent monitoring of herbivorous pest populations within the crop is a central component of IPM. This often requires extensive in-crop inspections or the installation and frequent assessment of insect monitoring traps, both of which are time- and labour-intensive (Ramsden et al., 2017). These challenges in herbivorous pest identification and monitoring can limit the extent to which farmers successfully implement IPM, or Agroecological Crop Protection.

Technological advances in herbivorous pest monitoring and prediction can support farmers by predicting pest migration and infestation (Leybourne et al., 2022), and by monitoring in-crop pest populations (Badgujar et al., 2023; Roosjen et al., 2020). There are several prediction tools that can help farmers estimate pest migration and crop risk within a given year (Leybourne et al., 2022, 2023; Tonnang et al., 2017). Herbivorous pest monitoring is often supported at regional or national scales, for example, through nationwide insect trap networks (Lagos-Kutz et al., 2020; Miao et al., 2011). Farmers primarily use these monitoring networks to time their own in-field monitoring efforts, although these efforts remain labour- and time-intensive (Ramsden et al., 2017). Remote imaging and image analysis are two technologies that are well-placed to be able to support farmers with in-field herbivorous pest monitoring and identification efforts, specifically by providing near real-time information on pest populations (remote imaging: Roosjen et al., 2020) and supporting identification efforts to confirm herbivorous pest presence (image analysis: Badgujar et al., 2023; Bjerge et al., 2023).

ARTIFICIAL INTELLIGENCE AND SUSTAINABLE AGRICULTURE

Artificial intelligence (AI) can be integrated into these remote imaging and image analysis technologies to develop smart and dynamic systems that can better support farmers. In this perspectives article we discuss how AI can be integrated into pest monitoring schemes to help with the implementation of sustainable agricultural practices. We discuss the potential of AI applications for sustainable agriculture primarily through the lens of using AI to assist with insect detection and predictive modelling, focussing on aspects of AI related to computer vision, deep learning and machine learning.

In these systems, AI represents the technology that underpins effective herbivorous pest detection, classification and quantification from data inputs (e.g., image capture or video data); the AI system can also support the decision-making process (Li et al., 2023; Yuan et al., 2023). AI can be used to support several aspects of IPM. Indeed, AI has recently been highlighted as a potential tool that can be used to support aphid monitoring (including detection and quantification) in agricultural systems (Batz et al., 2023). With regard to the eight IPM principles, AI could revolutionise the development and deployment of several IPM principles, including integration of AI into image-detection models to support pest identification (Principle 2); development of

TABLE 1 Overview of some available artificial intelligence-driven herbivorous pest detection systems that are based on algorithms trained on images collected under natural environments. For a more exhaustive list, please see Yuan et al. (2022).

Agricultural system (number of pests covered)	Country of development	Accuracy	Development conditions	Reference
Tea plantations (10 pests)	China	85.5%	Developed and tested using images collected in natural environments. Small dataset (40–72 images per species).	Deng et al., (2018)
		93%	Developed models using the Deng et al., 2018 image dataset.	Wang et al., (2019)
		95%		Nanni et al., (2020)
		99%		Dewi et al., (2023)
Banana plantations (Six pests and disease)	Africa and India	70%–99%	Developed and tested using images collected in natural environments. Large dataset (18,000 images).	Selvaraj et al., (2019)
Longan orchards (One stink bug)	Taiwan	90%–92%	Developed and tested using images collected in natural environments. Small dataset (849 images, increasing to 5000 after artificial augmentation)	Chen et al., (2020)
Beans and pea (Two beetles)	Mexico	76%–89%	Developed and tested using images collected in natural environments. Small dataset (75–200 images per species).	Roldán-Serrato et al., (2018)
Cereals (Focus on aphids)	United Kingdom (includes some pest images collected in China)	42%–75%	Developed and tested using images collected in natural environments. Large dataset (20,000 images).	Li et al., (2023)

AI-driven models that can better predict pest infestations (Principle 2); the integration of AI into library screening to identify novel bioactive compounds and the development of new pesticide chemistry (Principle 5); and the development of AI models that can better predict outbreaks of pesticide resistant populations (Principle 7). With regard to the second principle of IPM (pest identification and monitoring and prediction models; Barzman et al. (2015)), AI and AI-driven technologies are well-placed to support farmers through the development of 21st century IPM systems.

AI AND PEST MONITORING: ARE THERE OBSTACLES TO INTEGRATION AND UPTAKE?

Numerous AI-based pest identification technologies have been developed. With the majority of these focussing on herbivorous pest identification in specific agricultural systems, such as tea plantations (Deng et al., 2018), wheat and cereal crops (Badgujar et al., 2023; Li et al., 2023) and banana (Selvaraj et al., 2019). Table 1 summarises some of the available AI-driven pest identification technologies, focussing on examples that have been developed using images captured in natural environments. For a more extensive overview of herbivorous pest detection technologies, see review by Yuan et al. (2022).

AI-based decision-making is a process relying on ‘big data’. In other words, machines draw conclusions from a large volume of data and then apply these conclusions to real-world scenarios (Jarrahi, 2018). Compared with traditional decision-making models, AI technologies can deal with various complex environments and situations. The ability of AI, and by association AI-based computational technologies, to deal with complex scenarios enables these models to make robust estimations that are representative of the real world. Integrating machine-learning components into decision-making processes can produce more powerful tools, and this process has already been used to develop image analysis tools that can potentially support farmers with a range of agricultural tasks (Yuan et al., 2023).

There are several challenges and obstacles that limit the extent to which the resulting AI-based systems can be deployed under real-world scenarios. These obstacles need to be addressed and overcome if AI-driven 21st century IPM systems are to be developed and applied. We outline four obstacles below.

Obstacle 1: Model effectiveness. Machine learning techniques have been used to develop image-detection techniques that provide automated identification of insects from image data (Hansen et al., 2020; Mayo & Watson, 2007). These methods primarily work through a process of image collation, image annotation and AI model training. (Liu et al., 2019, 2021; Zhang et al., 2022). However, the underlying models can often run into accuracy and precision issues. The quality and resolution of the image, including the quality of the training images, is a significant factor influencing accuracy and precision that can also impact system effectiveness (Bereciartua-Pérez et al., 2023; Kamei, 2023; Roosjen et al., 2020). These obstacles can be addressed through preprocessing techniques, including image augmentation and cleaning, that can improve model performance. Reduced effectiveness of AI models is not directly due to low quality of images, but because of the size of pests and interference from complex nature environments. In previous work (Liu et al., 2019, 2021; Zhang et al., 2022), it has been illustrated that if the total size of pests in the image is above 1% of overall image resolution, then the accuracy of pest detection and counting could be up to 90%. Conversely, the accuracy of pest detection and counting reduces when this falls below 1%.

Obstacle 2: Functionality under field conditions. Several AI techniques are capable of detecting herbivorous pests (Faithpraise et al., 2013; Liu et al., 2019; Xie et al., 2015) and other arthropods (Hansen et al., 2020; Marques et al., 2018; Valan et al., 2019). However, many of these models have only been developed and tested on image libraries collated under controlled conditions. This represents a significant challenge in developing real-world solutions, as system success in controlled conditions will not necessarily translate to success under field conditions where external factors can reduce system effectiveness. Models that are developed and trained on image data that is primarily obtained under field-conditions are often reported to perform better under test scenarios (Ahmad et al., 2020; Gutiérrez et al., 2021). Therefore, by ensuring systems are trained on image and data captured under real-world natural environments they are better able to perform when deployed in the field. Indeed, effective systems have been developed for field-based identification of freshwater invertebrates (BIODISCOVER system; Høye et al., 2022) and for automated monitoring of moths in terrestrial environments (The UK Centre for Ecology & Hydrology AMI-trap platform).

Obstacle 3: Level of computational expertise and computational power required to use the system. Another obstacle to the uptake of these AI-based systems is end user operability. If the AI systems require significant computational knowledge, or are computationally intensive, they will not be seen as a feasible option for the majority of farmers and other end users. Similar obstacles are known to exist for standard computational pest prediction models (Leybourne et al., 2023); explainable AI is one potential solution that can facilitate farmer and end user accessibility to AI (Coulibaly et al., 2022). These obstacles can also be overcome by reducing the computational power needed to run the system, or by running it via external servers held on cloud platforms (Li et al., 2023); reducing computational power reduces the computational requirements of the end user. A number of approaches can be used to develop higher performing models, such as Single Shot Detector (Liu et al., 2016), Faster Region-based Convolutional Neural Networks (Ren et al., 2015), Feature Pyramid Network (Lin et al., 2017) and extended variations of these modelling approaches (Dai et al., 2016). By using these techniques to increase model performance, the underlying techniques can also be implemented on standard smart devices that farmers are more comfortable with using, including mobile phones where the computational models can be run via cloud-computing systems (Li et al., 2023; Yuan et al., 2023). Creating a simple and ergonomic user-interface for the end user will promote accessibility and facilitate uptake by perspective end users. If AI systems are user-friendly and operable on smart devices that farmers are familiar and confident in using, they will likely have a greater chance of being integrated into a farmer's everyday IPM practices. Several automated or device-driven AI systems have been developed (Badgujar et al., 2023; Bjerge et al., 2023; Yang et al., 2023); however, further developments are required to ensure a balance between accuracy, efficiency and usability.

Obstacle 4: System mobility. AI-based systems that are mobile and deployable are more likely to be used by end users. Mobile systems, for example systems that run via a smart device (Yuan et al., 2023), are well-placed to support farmers as a tool that can support ad hoc pest identification and monitoring activities. Versatility in the deployment and usability of systems is likely to be a key driving force behind whether any system is used by farmers under real-world conditions. Systems that can be initiated and used on-the-go are more likely to support the dynamic working patterns experienced by farmers, and systems that can be rapidly initiated can provide support as and when needed. These on-the-go systems will support insect identification tasks, however, if these systems are further developed into deployable systems that can be installed as remote imaging stations within fields they could further support farmers through real-time herbivorous pest monitoring (Wang et al., 2021). Advances in this area should be focussed on developing tools and functionality in order to 'scale down' the process in order to provide farmers the capability, the convenience and the precision of the AI-based DSS on a mobile phone (Yuan et al., 2023) or a deployable AI-driven 'monitoring station'. The potential integration into herbivorous pest detection systems that are operable on smart devices means that in the future it will be possible for a farmer to conduct enhanced herbivorous pest monitoring ad hoc during routine crop walks.

Above we identify four common obstacles that potentially limit the uptake of AI systems. These correspond to four criteria, outlined below, that we believe need to be successfully met in order to develop an AI-driven system that can support farmers with herbivorous pest monitoring efforts. As a minimum the AI model and the integrated AI-pest monitoring system should be:

1. Based on an accurate and precise model;
2. Adaptable and usable under real-world scenarios;
3. User-friendly, 'device-driven' and low-cost;
4. Mobile and deployable.

Transparency and reproducibility of AI are also key obstacles that will impact the development and uptake of these systems. Amongst others, these obstacles include access to and reproducibility of underlying code and the development of an open and transparent research and innovation community. However, as the targeted end users of AI-enabled pest management support are farmers and agronomists, we have focussed our obstacles and challenges around the development and uptake of usable systems by the end user.

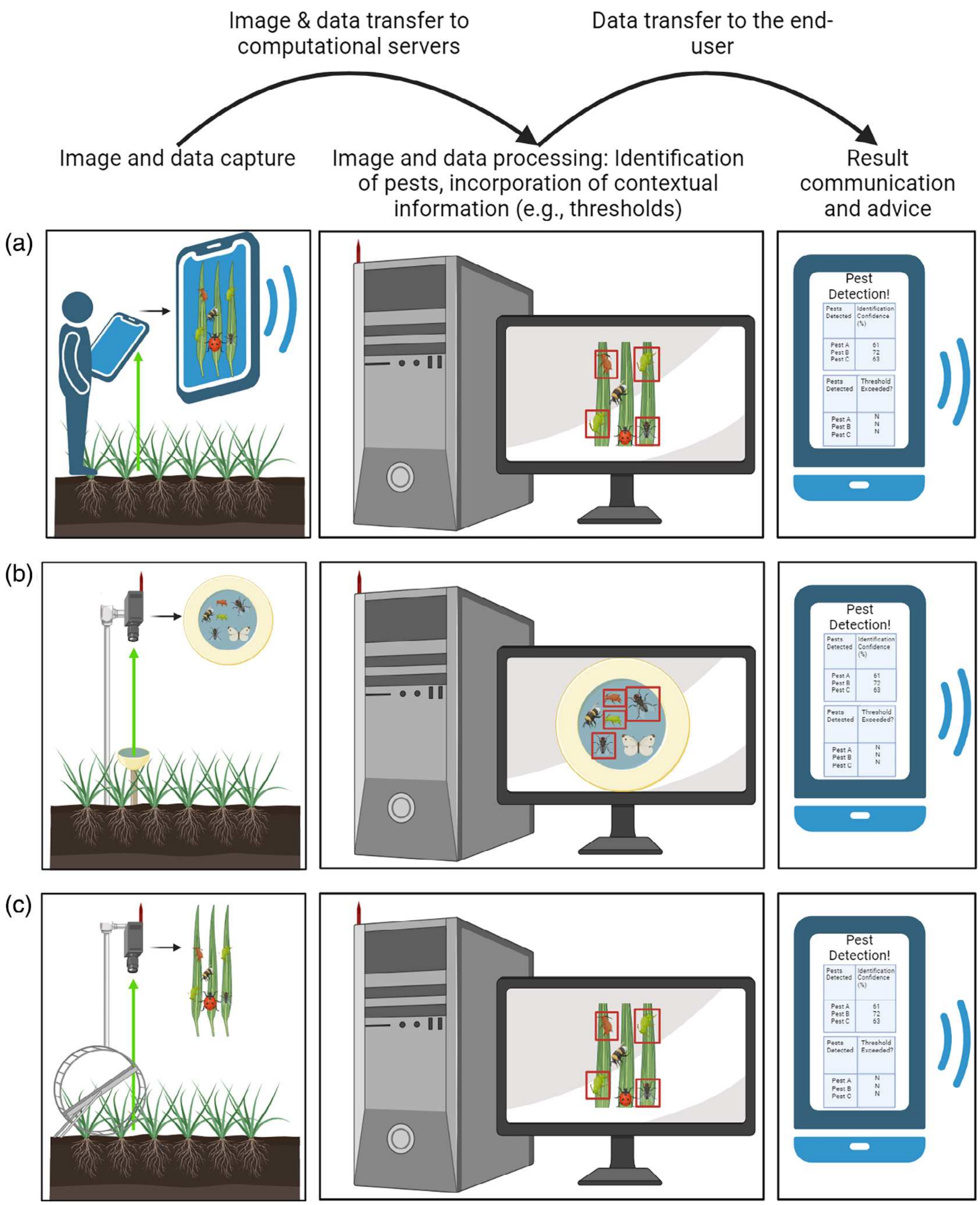

FIGURE 1 Graphical overview showing how artificial intelligence-techniques can be integrated with automated detection, classification and quantification of insect pests to develop smart herbivorous pest monitoring systems. (a) A mobile smart system supports farmers with ad hoc herbivorous pest identification; (b) A remote imaging station captures images from in-field traps; (c) A mobile monitoring station captures images from the crop canopy. All systems transmit images to a computer server where AI-driven models identify pest species present in the image and provide the end user with an output that can be used to guide decision-making processes. Image created with BioRender.com. Adapted from Leybourne et al. (2023).

INTEGRATING IMAGING AND AI FOR REAL-TIME ON-FARM PEST MONITORING

There are several avenues through which imaging technology, AI-driven image analysis techniques and IPM requirements for herbivorous pest monitoring can be combined to develop integrative systems that support farmers. The main avenue through which these are currently being combined is via the development of smart AI-driven herbivorous pest monitoring systems (Badgujar et al., 2023; Li et al., 2023; Yuan et al., 2023). Herbivorous pest monitoring systems that can capture automated near real-time pest images and transmit these images, alongside contextual data (e.g., environmental information), to computational servers to develop deployable herbivorous pest monitoring systems that can support farmer activities, including automated and sustained herbivorous pest monitoring.

One avenue that is currently being explored by our team is the development of on-the-go systems that run on routine smart devices, these systems are able to support farmers through AI-driven image detection and provide support with herbivorous pest identification during crop walks (Figure 1a; Li et al. (2023); Yuan et al. (2023)). Other systems could include fixed camera stations that are deployed by farmers alongside standard herbivorous pest traps (e.g., water traps), with images regularly passed to computational servers running AI-driven herbivorous pest detection models (Figure 1b). Stations could also comprise fully deployable pest monitoring stations that monitor herbivorous pest abundance and activity within the crop canopy (Figure 1c), for example, the Wild Pest Monitoring Station proposed by Wang et al. (2021) and the BIODISCOVER system proposed by Høye et al. (2022); these systems would also support automated near real-time herbivorous pest monitoring. AI-driven herbivorous pest identification techniques could then identify and quantify any herbivorous pests present in images captured during a crop walk (Figure 1a), in insect traps (Figure 1b) or in the crop canopy (Figure 1c). This would enable automated near real-time collection and assessment of trap contents and support sustained herbivorous pest monitoring at a given location, enabling farmers to target pest management interventions more precisely when thresholds are breached. Trap stations could be coupled with insect pheromone trapping to monitor specific herbivorous pests in a more specific manner: A system combining pheromone traps, automated imaging and AI-based pest identification has been developed to monitor and detect *Cydia pomenella* (Codling moth) in apple orchards (Mazare et al., 2019).

Integrating AI models into on-the-go smart devices and deployable in-field monitoring systems (Figure 1) would represent the next-step in utilising AI models in herbivorous pest management systems and fully integrating AI into a central IPM principle. Furthermore, as some of these systems (Figure 1b,c) collect automated near real-time insect trap data, additional image-detection models could also be integrated to monitor non-pest species, including beneficial arthropods. These integrated systems would also enable highly precise monitoring of insect phenology and migration at a high-resolution temporal scale.

Aerial imaging, for example, remote imaging by a drone or unmanned aircraft vehicle (UAV), is a further option that could support ad hoc herbivorous pest monitoring. Aerial surveys with UAVs can be used to detect immobile stages of the moth *Monema flavescens* and also distinguish between open and closed cocoons (Park et al., 2021). UAV has also been used to locate and identify the mobile instar of *Halyomorpha halys* (Sorbelli et al., 2023). These studies highlight the potential of UAVs for direct herbivorous pest detection in agriculture and early pest detection to prevent pest outbreaks. These systems are also useful for tracking and monitoring herbivorous pest migration across larger spatial scales (Abd El-Ghany et al., 2020).

Integrating AI into an effective and efficient IPM system will also depend on successfully managing edge device issues, such as cloud computing and Internet accessibility. Typically, these issues can be addressed by connecting devices to back-end servers that deploy the AI models to process the data and make the decision (Li et al., 2023; Yuan et al., 2023). However, in situations where infrastructure is poor deployment of these systems could be limited. Internet connectivity and accessibility can be addressed by developing lightweight AI models that can run on mobile or portable devices without requiring Internet access (Li et al., 2023; Yuan et al., 2023). Alternatively, for image-detection AI systems, the smart device could also transfer images to a cloud computing system once connectivity is restored (Karar et al., 2021).

PERCEIVED CHALLENGES IN INTEGRATING AI INTO A 21ST CENTURY INTEGRATED PEST MANAGEMENT SYSTEM

Integrating AI into IPM can support and improve herbivorous pest control by acting as an effective and reliable warning system for herbivorous pest outbreaks and threshold breaches. However, there are several challenges that need to be addressed before AI can be fully integrated into IPM systems. These include entomological, pest management and computational challenges.

Challenges from an entomological perspective

Taxonomic classification

The difficulty in assigning a correct taxonomy increases exponentially as the taxonomist, or the AI, moves down the taxonomic tree towards a species-level classification (Valan et al., 2019). Currently, the main pitfalls for integrating AI into pest management schemes are the taxonomic challenges associated with developing and training computational models that can accurately, precisely and reliably identify and quantify herbivorous pests. As a minimum, in order to have real-world implications any AI technology that aims to be integrated into an IPM system should be able to differentiate and quantify individual arthropods to a satisfactory resolution that is capable of providing agriculturally relevant information, where possible this technology should also be trained and developed using real-world 'field' images to ensure they can make these predictions under suboptimal conditions. Furthermore, a related challenge is the successful differentiation of a pest from a taxonomically similar, but agriculturally beneficial, insect; if an automated AI system incorrectly classifies a beneficial insect as a pest this could significantly lower farmer confidence in the tool. In order to develop fully automated AI-driven pest monitoring schemes, these challenges need to be addressed. Recent work has highlighted some of these challenges, and simultaneously identified computational methods through which these can begin to be addressed (Yuan et al., 2023).

The applicability of the system within an ecosystem context

Agricultural ecosystems are inherently complex ecological networks comprising herbivorous pest species, their natural enemies and the environment (Zu et al., 2023). Most AI technologies have focused solely on the identification of 'pests' and have neglected agricultural ecosystem complexity. Incorporating the wider ecological network will enable systems to account for the presence and absence of natural enemies, and will support farmers in working towards more sustainable management practices. The behaviour and spatial location of the herbivorous pest is also a key factor to consider. Herbivorous pests can conceal themselves from predators in areas that are not readily visible when observing the crop canopy from a top-down perspective, such as beneath leaves, leaf sheath or within the soil. Therefore, systems designed to assess herbivorous pest abundance and crop risk through the acquisition and analysis of top-down images might not fully capture the 'real' extent of herbivorous pest pressure and fall short as an alternative to a crop walk.

Challenges from a pest management perspective

Translating thresholds into correlated variables that can be detected with an AI system

Herbivorous pest thresholds are critical components of IPM systems, providing guidelines for when pest control measures should be implemented. However, some thresholds rely on crop damage rather than herbivorous pest abundance. For example, current thresholds for cabbage stem flea beetles (*Psylliodes chrysocephala*) are based on the percentage of leaf area damaged—50% of the leaf area damaged when crops are at growth stage 13 and 14 (Ellis et al., 2014). This poses a challenge for AI-based herbivorous pest monitoring systems as most AI technologies are developed to identify and quantify pests, not assess the damage they cause. Developing hybrid systems that combine AI-based pest monitoring with traditional monitoring methods, such as pest scouting and damage assessment, should create more comprehensive and effective AI-driven IPM systems. Further fieldwork is also required in order to relate thresholds that are compatible with AI systems (e.g., herbivorous pests per leaf) with thresholds that are currently followed (e.g., leaf damage).

Farmer perspective: Do they want it, do they need it, will they use it, will they trust it?

Despite the promise of smart farming technologies, including AI-based IPM, farmers may not necessarily be eager to adopt it (Adereti et al., 2024). Farmers are less convinced of smart farming technologies when it comes to specific on-farm challenges, and are hesitant regarding smart farming technology adoption (Kernecker et al., 2020). Several factors contribute to this reluctance: Traditional farming practices are deeply rooted in cultural practices, and this can create resistance against the adoption of AI technology, which is often perceived as disruptive (Adereti et al., 2024). Farmers often rely on their own expertise and lived experience to make informed decisions, and AI's reliance on data-driven insights may raise concerns about its accuracy and reliability, especially when the underlying algorithms are not transparent. To overcome these challenges and promote broader adoption of AI-powered IPM, farmers need access to accessible and tailored training programmes or demonstration to understand AI-based IPM principles, potential benefits and practical application coupled with farmer-friendly AI interfaces.

Challenges from a computational perspective

Deep learning techniques show outstanding performance with regard to herbivorous pest detection, and this can be used as a backbone to support the development AI-driven IPM systems. However, there are a set of key technical challenges associated with using these techniques to develop desirable pest management systems.

Accurate detection and effective classification of multiple crop pests in natural scenes

The task of detecting multiple crop pests in natural scenarios has some inherent feature extraction challenges, for example, the plethora of classification targets requires a feature extractor to be able to extract recognisable features. In addition, intuitive features of pests (e.g., texture, shape or colour) can be easily confused with background information, while features of tiny pests (e.g., rotation, zoom and panning) are too weak and insensitive to be recognised. There is a technical challenge on how to design an effective and robust AI model for multiple crop pest detection in the wild fields through effective learning methods.

Efficient and lightweight pest detection models in low-cost settings

The accuracy of deep learning models relies on a large number of trainable parameters for fitting complex non-linear relationships. However, the large number of parameters undoubtedly increases the memory and computational resource requirements during model computation, which significantly increases the cost of computing devices. Therefore, it is a technical challenge to lighten the model and increase the detection speed without losing detection accuracy through knowledge distillation and model quantisation. Cost associated with the use of decision support systems has recently been highlighted as a key obstacle against farmer uptake of these systems (Adereti et al., 2024), so this also represents a user-need challenge.

There are also aspects of computational power that represent a challenge when developing and designing usable systems. During the model design process, it is possible to minimise the number of model parameters to improve the efficiency of model calculation (Hou et al., 2018; Mostafa et. al., 2019). Mostafa et al. (2019) proposed an effective model design strategy to reduce the number of model parameters and computational requirements without loss of accuracy, achieved through the introduction of convolutional structures that can be easily reparametrised. Similarly, Hou et al. (2018) proposed a strategy to reduce the computational requirements by converting long floating-point weights that are computationally and memory-intensive into integers to reduce the high requirements on hardware without loss of precision.

Generation of sustainable and economically efficient pest management advice

Current AI-enabled decision support systems for herbivorous pest management normally rely on predetermined criteria to measure insect abundance and relate this to the economic threshold for the detected insect. The systems then use this information to provide optimal pest management advice. These systems could be further improved by better incorporating additional conextual information, such as environmental data, that could be used to produce more efficient and sustainable guidance for growers.

Societal and agricultural benefits

Economic benefits

Using AI technology for pest management decisions in cropping systems offers several long-term benefits for both the economy and the environment. Some benefits include the optimal utilisation of resources and time, reducing production costs (achieved through AI-driven support in pest detection and monitoring); accurate pest identification and alignment with current thresholds can also reduce the need for management interventions and further reduce the use of resources, time and costs.

AUTHOR CONTRIBUTIONS

Daniel J. Leybourne: Conceptualization; funding acquisition; visualization; writing – original draft. **Nasamu Musa:** Conceptualization; funding acquisition; writing – review and editing. **Po Yang:** Conceptualization; funding acquisition; writing – review and editing.

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DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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