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REVIEW

Selective protection of cereals using artificial neural networks

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Abstract

Global agricultural losses due to pests and pathogens are substantial, particularly for wheat, maize, and potatoes. Addressing these challenges necessitates innovative approaches in plant protection, particularly through early detection methods. This article outlines research areas concerning the application of spectral imaging technologies in selective crop protection processes. Recent technological advancements, driven by the development of high-resolution optical sensors and data analysis methods (Pena *et al.* 2013), have enabled early detection of weeds, plant diseases, and pests in the field. Spectral imaging technologies, particularly hyperspectral imaging, play a pivotal role in early disease detection by capturing detailed spectral data across a wide range of wavelengths. This technology enables the detection of subtle physiological changes in plants long before visible symptoms occur. Hyperspectral imaging has proven effective in identifying diseases such as Fusarium head blight in wheat, allowing for timely interventions and potentially reducing yield losses. The integration of hyperspectral imaging with remote sensing technologies, including unmanned aerial vehicles and ground-based sensors, as well as artificial intelligence represents a significant advancement in precision agriculture. This multidisciplinary approach aims to enhance crop protection while minimizing environmental impacts. The article also explores the advantages and limitations of these technologies and strategies for reducing the reliance on chemical plant protection methods in agricultural production. It is underlined, that future research should focus on optimizing these technologies, addressing cost barriers, and exploring UAV-based applications for precision spraying and monitoring.

Keywords: artificial intelligence (AI), early disease detection, precision agriculture, remote sensing, spectral imaging, unmanned aerial vehicles (UAVs)

Introduction

The primary objective of the European Union's "Farm to Fork" strategy is to ensure the availability of high-quality, sustainable food across Europe. This ambitious strategy, central to the European Green Deal, seeks to transform the European food system to ensure environmental and human health benefits. A critical target within this strategy is the 50% reduction of the use of chemical plant protection products by 2030. This goal addresses growing concerns about the long-term effects of pesticide overuse, which have been linked to environmental degradation, biodiversity loss, and negative health impacts on humans (Huded *et al.* 2023).

The gradual withdrawal of active substances in plant protection products from the market poses significant challenges for European farmers. As more substances are phased out, the range of available chemical plant protection tools narrows, increasing the risk of yield losses due to pests and diseases. A potential solution lies in the adoption of precision plant protection technologies, which utilize advanced methods such as artificial intelligence (AI), remote sensing, and digital tools to optimize the use of pesticides. These technologies can target specific areas of a field, applying treatments only where necessary, thereby reducing the overall amount of chemicals used (Gebbers and Adamchuk 2010).

Excessive pesticide use not only leads to environmental degradation but also contributes to the contamination of food products, negatively affecting human health. Multiple studies have shown that long-term exposure to pesticides, even in small quantities, can lead to chronic diseases such as cancer, reproductive disorders, and neurodegenerative conditions (Mostafalou and Abdollahi 2017). Thus, reducing pesticide usage benefits producers, consumers, and the environment alike. Given these advantages, the development and implementation of precision plant protection technologies have become a key task for modern agriculture. Scientific research should focus on these innovations to ensure sustainable and effective plant protection in the future (Monteiro *et al.* 2021).

In recent years, agricultural digitalization has gained significant impact. One promising research area involves the integration of precision technologies with AI models and remote sensing tools, which offer real-time monitoring and decision-making support for farmers. The Rural Development Program 2014–2020 (PROW) was developed by the Ministry of Agriculture and Rural Development in Poland. Based on European Union regulations, in particular, Regulation (EU) No. 1305/2013 of the European Parliament and Council, on December 17, 2013, in support of rural development, the European Agricultural Fund for Rural Development (EAFRD) repealed Council Regulation (EC) No. 1698/2005. It also delegated and implemented acts of the European Commission which provided a substantial opportunity to enhance agricultural innovation through the "Cooperation" measure. This initiative supported the formation of consortia in the form of Operational Groups, which brought together agricultural advisory services, research institutions, and farmers to collaborate on technological advancements in agriculture (Bomberski 2020). In Poland, cooperation between advisory bodies and scientific institutions has led to the creation of 438 Operational Groups, with approximately 40 focusing on the digitalization of agriculture, a trend known as Agriculture 4.0. These groups have facilitated the collaboration of over 1200 entities, driving the transfer of knowledge and innovative solutions into agricultural practices and advisory services (Bomberski 2023). Among these, the Teledis Group has made significant contributions to digitalization projects, including those discussed in this article.

Polish agriculture requires sustained financial interventions and focused research to support multi-actor collaboration, according to the European Commission recommendations. This multi-actor approach involves the participation of various stakeholders (farmers, researchers, advisory bodies, and industry experts) in the development of new technologies. It increases the likelihood of successful innovation by fostering collaboration from the concept phase through research, testing, validation, and implementation. For Poland to enhance its agricultural competitiveness and profitability, it is essential to introduce digital solutions and innovations into everyday agricultural practice. One of the first steps in this direction is the effective protection of crops, coupled with a reduction in chemical pesticide use through the application of digital precision technologies.

The current state of knowledge

The global scientific community has shown increasing interest in artificial intelligence (AI) and its applications across various sectors, including agriculture. According to the Scopus database, by September 2024, around 597,832 scientific articles had been published on the topic of AI. Specifically, in the context of plant science, 6,130 publications focused on the use of hyperspectral imaging for plants. When the keyword "disease" was included, 720 publications were found, with 90 focused on identifying wheat diseases. This indicates the growing relevance of AI in solving complex challenges in modern agriculture.

The development of artificial neural networks (ANNs) since the 1950s has been a critical advancement in this field. Battleday *et al.* (2021) highlight three key stages in the evolution of ANNs: early exploratory stages, the rise of machine learning in the late 20th century, and the current era of deep learning and cognitive systems. Cognitive systems are capable of understanding and responding to natural language, making them suitable for human-computer interaction in complex environments such as agricultural decision-making (Goodfellow *et al.* 2016). Deep learning, an advanced subset of machine learning, allows ANNs to process large datasets and solve intricate problems such as image recognition, which has become invaluable in diagnosing plant diseases (Chen *et al.* 2020; Cravero *et al.* 2022).

In the domain of plant protection, many studies have focused on identifying cereal diseases using multispectral and hyperspectral cameras or fluorescence visualization methods often combined with neural network architectures (Szechyńska-Hebda *et al.* 2015; Lowe *et al.* 2017; Lu *et al.* 2017; Dyda *et al.* 2019; Qiu *et al.* 2019; Singh *et al.* 2020; Wan *et al.* 2022; Wąsek *et al.* 2022). Hyperspectral imaging is capable of detecting subtle physiological changes in plants before visible symptoms appear, allowing for early diagnosis and prevention (Mahlein *et al.* 2018). Among the most significant threats to global wheat production is Fusarium head blight (FHB), caused primarily by *Fusarium graminearum,* however, other *Fusarium*-related diseases also can impact final yield (Szechyńska-Hebda *et al.* 2011; Dyda *et al.* 2019; Bartosiak *et al.* 2021). The disease can lead to yield losses of up to 80%, making early detection crucial for mitigating their impact (Ma *et al.* 2021).

Artificial intelligence has emerged as an important tool in addressing these challenges, particularly in the optimization of plant protection strategies. However, the rapid development of AI technologies shortens the lifecycle of AI-related projects (Sajid 2023). Maintaining these systems is becoming increasingly complex, as applications require continuous updates to datasets, model improvements, and technical support. This complexity can hinder the practical adoption of AI technologies in agriculture, particularly in regions with limited financial and technical resources. In Poland, the adoption of modern AI-based plant protection systems is still in its early stages, e.g., AI-based applications for detecting wheat and triticale diseases remain limited in scope, detecting only visible disease symptoms (Golka *et al.* 2020, 2024a, 2024b).

Simultaneously, major international companies such as Bosch, Bayer, and Agrifac are developing digital technologies for precision spraying. Bosch and Bayer have created sprayers equipped with cameras spaced every meter along the boom, designed to recognize weed species. Agrifac has introduced systems that use cameras to determine the precise doses of liquid applied to each nozzle, while Blue River Technology has developed a system to prevent liquid drift by controlling many nozzles individually (Zanin *et al.* 2022).

There is an increasing need for early disease detection technologies. Research is ongoing to develop spectral imaging technologies that can identify plant diseases at earlier stages of development before symptoms are visible to the naked eye (Zhang and Kovacs 2012; Ma *et al.* 2021). Although promising, most of these technologies are still in the laboratory phase, with only a few field applications. Their integration into practical agriculture, particularly in Poland, remains a challenge.

Directions for research in digital crop protection technologies

Global agricultural losses due to pests and pathogens are substantial, yearly averaging 21.5% for wheat, 22.5% for maize, and 17.2% for potatoes (Savary *et al.* 2019). These losses not only affect farmers economically but also threaten global food security. As a result, plant protection research has increasingly focused on early detection methods that can stop the spread of diseases before they cause significant damage.

Spectral imaging technologies are among the most promising tools for early disease detection. These methods capture images across multiple wavelengths, revealing physiological changes in plants that are invisible to the naked eye (Mahlein *et al.* 2018). Researchers have reported highly positive results from the application of spectral imaging for plant disease detection. Hyperspectral imaging has proven effective in detecting diseases like Fusarium head blight in wheat, which can devastate crops if left unchecked (Ma *et al.* 2021; Wan *et al.* 2022; Gao *et al.* 2023).

Detection begins with capturing detailed spectral images of crops, followed by preprocessing to cluster and analyze the data. Various imaging techniques are employed, including thermal, multispectral, fluorescence, hyperspectral, and visible light imaging. These images provide essential information for training neural networks, which can learn to recognize disease patterns at different stages of development (Singh *et al.* 2020). For example, hyperspectral and fluorescence imaging can detect chlorophylls breakdown or other pigment indicators before they become visible (Bauriegel *et al.* 2011; Szechyńska-Hebda *et al.* 2015; Dyda *et al.* 2019; Poobalasubramanian *et al.* 2022; Szechyńska-Hebda *et al.* 2022; Jie *et al.* 2023). However, a fundamental understanding of plant physiology, photosynthesis, and biochemistry is crucial for effectively utilizing these imaging technologies. By leveraging basic knowledge of these physiological processes and the biochemical properties of plants, researchers can interpret the spectral data more accurately (Szechyńska-Hebda *et al.* 2011; Karpiński and Szechyńska-Hebda 2023). The physiological knowledge helps in assessing the plant's responses to various stressors and diseases, providing insights that enhance the precision of early detection methods (Szechyńska-Hebda *et al.* 2011, 2015; Dyda *et al.* 2019; Galieni *et al.* 2021; Moustaka and Moustakas 2023). Furthermore, by understanding mechanisms of plant reactions to stress, scientists can refine imaging techniques and develop more effective strategies for plant protection. Furthermore, research into digital crop protection technologies benefits greatly from integrating insights from plant monitoring, physiology, biochemistry, and genetics (Bartosiak *et al.* 2021; Karpiński and Szechyńska-Hebda 2023; Koshariya *et al.* 2023). Such integration allows for a more comprehensive evaluation of plant responses and improves the interpretation of imaging data. By starting with a solid grasp of how plants interact with their environment and respond to stress, researchers can advance the development of diagnostic tools and protective measures. This approach not only enhances the accuracy of disease detection but also supports the creation of more targeted and efficient plant protection strategies, ultimately contributing to sustainable agricultural practices.

The future development of digital crop protection technologies requires a multi-disciplinary approach that combines advances in remote sensing, AI, and deep plant physiology. Ongoing research in this field is exploring ways to integrate these technologies into practical agricultural systems, enabling farmers to protect their crops more effectively while reducing the environmental impact of chemical treatments (Dasgupta *et al.* 2020). The successful implementation of such systems could revolutionize plant protection and significantly contribute to the sustainability of modern agriculture.

Hyperspectral imaging technology

Standard digital photography captures images in three electromagnetic wavelength ranges (400 nm to 700 nm), corresponding to the B (blue) G (green), and R (red) channels (RGB). This technique, while valuable, is limited in its diagnostic capabilities. Although, artificial neural networks (ANNs) can diagnose wheat diseases using standard RGB images, it is only possible when the disease is advanced and visible to the naked eye (Cooper *et al.* 2023). However, by the time visual symptoms are detectable, the damage may already be extensive, reducing the effectiveness of subsequent interventions.

In contrast, hyperspectral imaging offers a much broader range of information. A hyperspectral camera records spectral reflectance over more than 100 narrow electromagnetic wavebands, ranging from 400 nm to 2,500 nm, covering both the visible and infrared spectra (VIS–NIR–SWIR). This enables the detection of subtle physiological changes in plants long before symptoms are visible to the human eye (Mahlein *et al.* 2012, 2013). The ability to capture such fine detail allows for earlier diagnosis, leading to more timely interventions and potentially reducing yield losses.

Each hyperspectral image recorded by the camera has a resolution of ~4 nm. This narrow slice of reflected light provides insights into details, such as chlorophyll breakdown or water stress. In the infrared spectrum, which spans wavelengths from about 700 nm to 2,500 nm, the reflection and absorption of infrared light by plants reveal important physicochemical properties, such as water content, cell structure, and stress responses, making hyperspectral imaging a valuable tool in precision agriculture (Thenkabail *et al.* 2000).

The analysis of these spectral bands also allows for the differentiation between various plant stresses, such as biotic (pathogen or pest infestation) and abiotic (drought, nutrient deficiencies) factors (Behmann *et al.* 2015a, 2015b). This makes it particularly useful in precision plant protection, where early detection and accurate identification of the stress factors are critical for effective treatment.

Numerous models of hyperspectral cameras are currently available, each capable of capturing different ranges of spectral data. The technology can be customized to target specific wavebands of interest, depending on the crop type and the specific threats being monitored. However, the successful application of hyperspectral imaging in agriculture requires a thorough understanding of the spectral signatures of different stressors. For instance, spectral variations caused by *Fusarium* infection in wheat differ from those caused by water stress, and differentiating between such stressors requires a robust dataset of spectral patterns (Khanal *et al.* 2017).

A significant limitation of hyperspectral imaging technology is its costs. The price of hyperspectral cameras remains a threshold for many small and medium-sized farms, and their widespread adoption may require financial support or subsidies. Furthermore, the data complexity and volume generated by hyperspectral imaging can be overwhelming. To mitigate this, spectral vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), are often used to simplify data analysis and improve processing speed while maintaining diagnostic accuracy (Camps-Valls *et al.* 2021; Pasternak and Pawłuszek-Filipiak 2022).

Bauriegel *et al.* (2011) identified growth stages GS 71–85 on the BBCH scale as the optimal period for detecting plant diseases in wheat using hyperspectral imaging (e.g., Fusarium head blight, a fungal disease that primarily affects the heads). On the other hand, hyperspectral reflectance and brightness measurements, taken 37 days after *Zymoseptoria tritici* infection (Septoria tritici blotch) and 30 days after *Phaeosphaeria nodorum* infection (Stagonospora nodorum blotch), provided precise assessments of disease damages in advanced stages of crop development (Zhelezova *et al.* 2023). These specific timeframes were critical for accurately quantifying disease impact and providing information about targeted intervention strategies. In similar research, hyperspectral imaging was used to monitor the progression of yellow rust in wheat (Bohnenkamp *et al.* 2019), achieving effective disease detection by early May (BBCH 31). After mid-May (BBCH 37–39), with favorable dew conditions induced by warm days and cool nights, yellow rust had become the predominant disease affecting the crop, marking a stage too advanced for preventative intervention. These studies collectively underscore the necessity of aligning detection efforts with specific plant growth stages to optimize the efficacy of disease identification. The BBCH scale, a widely recognized system that employs decimal coding to denote plant developmental phases, provides a standardized framework for monitoring disease progression in cultivated plants and weeds (Lancashire *et al.* 1991; Pena *et al.* 2013). Implementing hyperspectral imaging at these critical growth stages enhances early disease detection and facilitates timely, targeted interventions, reinforcing the method's role in modern plant pathology and crop management aimed at preserving plant health and yield potential.

Variants of digital technologies for selective plant protection

Digital technologies for selective plant protection have evolved rapidly in recent years, driven by advances in AI, machine learning, and remote sensing technologies. Current research has highlighted two primary approaches to field-based selective plant protection technologies:

1. Remote sensing using unmanned aerial vehicles (UAVs).
2. Proximal sensing from ground-based equipment.

Remote sensing via UAVs offers the advantage of covering large areas quickly and cost-effectively. UAVs equipped with hyperspectral or multispectral cameras can capture detailed images of crop fields, allowing for the early detection of diseases, pests, and nutrient deficiencies (Zhang and Kovacs 2012; Nguyen *et al*. 2021). The ability to monitor large fields from above reduces labor costs and provides real-time data, which can be crucial for timely interventions (Hunt *et al.* 2010).

In contrast, proximal sensing, typically involving ground-based equipment such as tractors or sprayers fitted with cameras and sensors, provides higher-resolution data but may be more time-consuming (Tona *et al.* 2018). Ground-based systems are often more precise because they operate closer to the plants, allowing for detailed analysis of individual plants or small groups (Qiu *et al.* 2019). Both remote and proximal sensing techniques are essential components of precision agriculture, where the goal is to maximize crop yields while minimizing inputs water, fertilizers, and pesticides (Roberts 2021).

A third variant involves the use of UAVs for spraying crops, although this is currently limited by the European Union regulations that prohibit drone-based spraying. Nonetheless, UAVs offer several advantages over traditional ground-based sprayers. They can avoid damaging tall crops, prevent soil compaction caused by tractor wheels, and access areas that are difficult to reach, such as waterlogged fields. However, UAV operations are highly dependent on weather conditions, which can limit their use during windy or rainy periods (Cieślik 2023).

Despite these regulatory hurdles, there is growing interest in the use of drones for precision spraying, and ongoing research in Poland aims to address these legislative barriers. The integration of UAV-based spraying with AI-driven monitoring systems holds significant promise for future developments in precision agriculture, offering both environmental and economic benefits (Zhang and Kovacs 2012).

In the following sections, the potential of UAV-based technology for plantation monitoring using hyperspectral cameras will be explored. This variant is particularly conducive to research focused on the early detection of plant diseases, enabling more efficient and sustainable plant protection strategies. There are plans to further investigate this approach under the NCBR's "Infostrateg VI" project no. INFOSTRTEG 6/0014/2023/A "Artificial Intelligence for the identification of undesirable phenomena and selective crop protection" (Akronim: AI4Crop).

Selective plant protection technology using artificial neural networks (ANN) and UAVs

The primary objective of the proposed AI4Crop technology is to develop and field-test a selective plant protection system that integrates UAVs with ANN for early disease detection. Early detection of plant diseases is critical for minimizing damage and reducing the need for chemical treatments. By integration, the system aims to provide a more accurate and efficient means of monitoring and protecting crops. The key components of this system (Fig. 1) include:

- pattern database;
- monitoring system;
- artificial neural network (ANN) module;
- crop threat maps;
- upgraded field sprayer.

Pattern database

The pattern database is the applying of the ANN's ability to detect diseases early. It serves as a collection of training data for the ANN, enabling the differentiation between biotic threats (e.g., pathogens, pests) and abiotic stresses (e.g., drought). The database includes spectral and RGB imaging of healthy and diseased crops, meticulously selected for their quality and

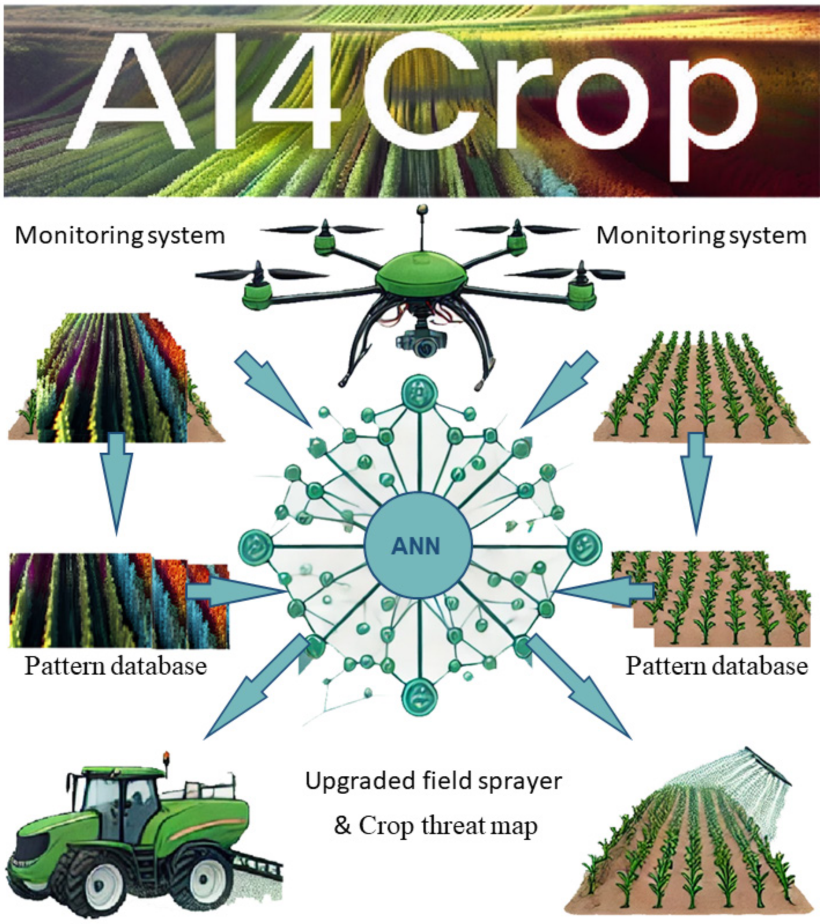

Fig 1. The goal of the AI4Crop project is to implement an innovative, individualized monitoring system that distinguishes crop responses to pathogens, pests, and drought. This system will utilize spectral imaging, coordinated by an Artificial Neural Network (ANN) to generate threat maps that categorize areas of the field into critical, endangered, and preventive zones. Eventually, an automated intelligent spraying system will be integrated with field sprayers. This system includes algorithms for selective spray control based on ortho-photomap data, as well as algorithms for positioning spray elements and determining their optimal trajectory

relevance to ANN training. This database must be continually updated and expanded as the ANN is refined and the variety of crops and diseases increases (Saleem *et al*. 2020; Garg *et al.* 2023).

The creation of a robust pattern database is a complex task, as it requires the accurate analysis of hyperspectral data. A well-structured database allows the ANN to compare new data with stored patterns, identifying disease symptoms early, often before they are visible to the naked eye (Mahlein *et al.* 2013). The success of this system hinges on the quality of the database, as the ANN's accuracy in diagnosing plant diseases directly correlates with the quality of the stored patterns.

Given the variety of crops and diseases, the database must be scalable. A potential solution is MongoDB, a popular NoSQL database management system known for its flexibility and scalability. MongoDB can store large datasets and handle the complexity of hyperspectral imaging data, making it well-suited for this application. Moreover, cloud-based storage solutions allow for continuous updating and expansion of the database, ensuring that the ANN can adapt to new threats as they arise (Chen *et al.* 2022).

Monitoring system

The monitoring system in this technology consists of a UAV equipped with a hyperspectral or multispectral camera. The UAV serves as a platform for high-resolution monitoring, flying over fields to capture data on crop health. The 'drones' have become increasingly popular in agriculture due to their ability to cover large areas quickly and provide detailed data (Zhang and Kovacs 2012).

The multispectral or hyperspectral camera mounted on the UAV is essential for detecting early disease symptoms. These cameras capture images in narrow spectral bands, allowing for the identification of subtle changes in plant physiology, such as water stress or the early stages of a fungal infection (Zaka and Samat 2024). The high resolution provided by these cameras ensures that even small areas of infection can be detected, allowing for targeted treatments rather than blanket applications of pesticides (Mahlein *et al.* 2018).

This early detection capability is crucial for precision agriculture, as it enables interventions that are both timely and localized. By identifying affected plants early, farmers can reduce the amount of chemical treatment needed, lowering costs, and minimizing environmental impact (Thenkabail *et al.* 2000).

ANN module

The neural network module is responsible for processing the data collected by the UAV and diagnosing plant health issues. The ANN is trained using the pattern database and is capable of identifying early disease symptoms that are invisible to the human eye. The early detection allows for more precise interventions, reducing the need for widespread chemical treatments (Baratov and Valixanova 2023).

Convolutional neural networks (CNNs), a type of ANN particularly well-suited to image analysis, are expected to be the most effective for this application. CNNs can identify key features in images, such as color and texture changes associated with early disease symptoms (Qiu *et al.* 2019). The ANN can categorize plants into three states: healthy, diseased, or other (for ambiguous cases), allowing for precise mapping of disease hotspots in the field.

Advantages and disadvantages of selective plant protection technology using ANN and UAV

The implementation of selective plant protection technology offers numerous functional, social, economic, and environmental benefits. One of the key functional advantages is its ability to detect diseases at an early stage, limiting their spread and reducing overall damage to crops. Additionally, the system's integration with ANN and hyperspectral imaging allows for a level of diagnostic accuracy that surpasses traditional methods (Barbedo 2016).

Functional Benefits:
- Detection of diseases at an early stage, allowing for timely intervention.
- Increased diagnostic accuracy compared to traditional methods.
- Comprehensive system integrating monitoring, diagnosis, and treatment.

Social Benefits:
- Improved food quality and safety by reducing chemical use.
- Alignment with global trends in sustainable agriculture and digitalization.

Economic Benefits:
- Reduction in chemical plant protection products by up to 30% (Jin *et al.* 2018).
- Lower costs of crop monitoring than traditional aerial or satellite methods.
- Prevention of yield losses through early intervention.

Environmental Benefits:
- Decreased chemical use, reducing environmental impact.
- More sustainable agriculture by lowering pesticide runoff and soil degradation.

Conclusions

1. A review of the literature indicates a growing interest in the digitalization of agriculture, particularly in the application of ANN and hyperspectral imaging for plant protection.
2. Research and development over the past decade have focused on reducing chemical inputs, improving disease detection, and automating plant protection processes.
3. While significant progress has been made in disease detection using hyperspectral cameras and ANN, these technologies have yet to be widely adopted in field agriculture due to their complexity and cost.
4. The proposed AI4Crop system represents a significant advancement in selective plant protection, offering early disease detection, precise interventions, and integration with existing agricultural practices.
5. Continued support for multi-actor projects, such as those under the PROW 2014-2020, is essential for the widespread adoption of these technologies.

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References

Baratov R., Valixanova H. 2023. Smart system for early detection of agricultural plant diseases in the vegetation period.

E3S Web of Conferences. DOI: https://doi.org/10.1051/e3sconf/202338601007
Barbedo J.G.A. 2016. A review on the main challenges in automatic plant disease identification based on visible range images. Biosystems Engineering 144: 52–60. DOI: https://doi.org/10.1016/j.biosystemseng.2016.01.017
Bartosiak S.F., Arseniuk E., Szechyńska-Hebda M., Bartosiak E. 2021. Monitoring of natural occurrence and severity of leaf and glume blotch diseases of winter wheat and winter triticale incited by necrotrophic fungi *Parastagonospora* spp. and *Zymoseptoria tritici*. Agronomy 11 (5): 967. DOI: https://doi.org/10.3390/agronomy11050967
Battleday R., Peterson J., Griffiths T. 2021. From convolutional neural networks to models of higher-level cognition (and back again). Annals of the New York Academy of Sciences 1505: 55–78. DOI: https://doi.org/10.1111/nyas.14593
Bauriegel E., Giebel A., Herppich W.B. 2011. Hyperspectral and chlorophyll fluorescence imaging to analyse the impact of *Fusarium culmorum* on the photosynthetic integrity of infected wheat ears. Sensors 11 (4): 3765–3779. DOI: https://doi.org/10.3390/s110403765
Behmann J., Mahlein A.K., Rumpf T., Römer C., Plümer L. 2015a. A review of advanced machine learning methods for the detection of biotic stress in precision crop protection. Precision Agriculture 16: 239–260. DOI: https://doi.org/10.1007/s11119-014-9372-7
Behmann J., Steinrücken J., Plümer L. 2015b. Detection of early plant stress responses in hyperspectral images. Remote Sensing 7 (4): 3872–3896. DOI: https://doi.org/10.1016/j.isprsjprs.2014.03.016
Bohnenkamp D., Behmann J., Mahlein A. 2019. In-field detection of yellow rust in wheat on the ground canopy and UAV scale. Remote Sensing 11: 2495. DOI: https://doi.org/10.3390/rs11212495
Bomberski M. 2020. The role of agricultural advisory services in implementing the objectives of the network for innovation in agriculture: a case study of the kuyavian-pomeranian voivodeship. PhD Thesis. Publishing House of the University of Technology and Life Sciences in Bydgoszcz.
Bomberski M. 2023. Implementing innovations and managing operational groups by innovation brokers within the Rural Development Program for 2014-2020 and the Common Agricultural Policy for 2023-2027. Publishing Group of the University of Economy in Bydgoszcz.
Camps-Valls G., Campos-Taberner M., Moreno-Martínez Á., Walther S., Duveiller G., Cescatti A., Mahecha M., Muñoz-Marí J., García-Haro F., Guanter L., Jung M., Gamon J., Reichstein M., Running S. 2021. A unified vegetation index for quantifying the terrestrial biosphere. Science Advances 7 (9): eabc7447. DOI: https://doi.org/10.1126/sciadv.abc7447
Chen J., Chen J., Zhang D., Sun Y., Nanehkaran Y. 2020. Using deep transfer learning for image-based plant disease identification. Computers and Electronics in Agriculture 173: 105393. DOI: https://doi.org/10.1016/j.compag.2020.105393
Chen Z., Yang X., Li F., Cheng X., Hu Q., Miao Z., Xie R., Wu X., Wang K., Song Z., Sun H., Zhuang Z., Yang Y., Xu J., Yin L., Zhou W. 2022. CloudJump: Optimizing Cloud Databases for Cloud Storages. Proceedings of the VLDB Endowment 15: 3432–3444. DOI: https://doi.org/10.14778/3554821.3554834
Cieślik R. 2023. Drones over Polish fields. Poznań University of Life Sciences. [Available on: https://puls.edu.pl/aktualno-ci/drony-rolnicze-nad-polskimi-polami] [Accession: May 15, 2024] (in Polish).
Cooper J., Du C., Beaver Z., Zheng M., Page R., Wodarek J., Matny O., Szinyei T., Quiñones A., Anderson J., Smith K., Yang C., Steffenson B., Hirsch C. 2023. An RGB based deep neural network for high fidelity Fusarium head blight phenotyping in wheat. bioRxiv. DOI: https://doi.org/10.1101/2023.09.20.558703
Cravero A., Pardo S., Galeas P., López Fenner J., Caniupán M. 2022. Data type and data sources for agricultural big data and machine learning. Sustainability 14 (23): 16131. DOI: https://doi.org/10.3390/su142316131
Dasgupta I., Saha J., Venkatasubbu P., Ramasubramanian P. 2020. AI crop predictor and weed detector using wireless technologies: a smart application for farmers. Arabian Journal for Science and Engineering 45: 11115–11127. DOI: https://doi.org/10.1007/s13369-020-04928-2
Dyda M., Wąsek I., Tyrka M., Wędzony M., Szechyńska-Hebda M. 2019. Local and systemic regulation of PSII efficiency in triticale infected by the hemibiotrophic pathogen *Microdochium nivale*. Physiologia Plantarum 165 (4): 711–727. DOI: https://doi.org/10.1111/ppl.12870
Galieni A., D'ascenzo N., Stagnari F., Pagnani G., Xie Q., Pisante M. 2021. Past and future of plant stress detection: an overview from remote sensing to positron emission tomography. Frontiers in Plant Science 11: 609155. DOI: https://doi.org/10.3389/fpls.2020.609155
Gao C.F., Ji X.J., He Q., Gong Z., Sun H., Wen T., Guo W. 2023. Monitoring of wheat Fusarium head blight on spectral and textural analysis of UAV multispectral imagery. Agriculture 13 (2): 293. DOI: https://doi.org/10.3390/agriculture13020293
Garg G., Gupta S., Mishra P., Vidyarthi A., Singh A., Ali A. 2023. CROPCARE: An intelligent real-time sustainable iot system for crop disease detection using mobile vision. IEEE Internet of Things Journal 10: 2840–2851. DOI: https://doi.org/10.1109/JIOT.2021.3109019
Gebbers R., Adamchuk V.I. 2010. Precision agriculture and food security. Science 327 (5967): 828–831. DOI: https://doi.org/10.1126/science.1183899
Golka W., Arseniuk E., Golka A., Góral T. 2020. Artificial neural networks and remote sensing in the assessment of spring wheat infection by Fusarium head blight. Biuletyn IHAR 288: 67–75. (in Polish)
Golka W., Szechyńska-Hebda M., Golka A., Kowalska J., Góral T. 2024a. Cereal health assessment system for farm. Topics in Agricultural Advisory Services (Zagadnienia Doradztwa Rolniczego) 1 (115): 98–118. (in Polish)
Golka W., Szechyńska-Hebda M., Golka A., Kowalska J., Góral T., Bomberski A. 2024b. Analysis of the Teledis system in the assessment of cereal health. Topics in Agricultural Advisory Services (Zagadnienia Doradztwa Rolniczego) 2: 123–135. (in Polish)
Goodfellow I., Bengio Y., Courville A. 2016. Deep learning. MIT Press. [Available on: http://www.deeplearningbook.org] [Accession: June 15, 2024]
Huded S., Savadatti E.H.,S., Deb L., Borah A., Singh V., Panigrahi C. 2023. Examining modern strategies for effective and sustainable agricultural plant protection techniques: A review. International Journal of Environment and Climate Change 13 (11): 1331-1343. DOI: https://doi.org/10.9734/ijecc/2023/v13i113285
Hunt E. R., Hively W. D., Fujikawa S. J., Linden D.S., Daughtry C.S.T., McCarty G.W. 2010. Acquisition of NIR-green-blue digital photographs from unmanned aircraft for crop monitoring. Remote Sensing 2 (1): 290–305. DOI: https://doi.org/10.3390/rs2010290
Jie Z., Wang Q., Song G., Jin J. 2023. Validating and developing hyperspectral indices for tracing leaf chlorophyll fluorescence parameters under varying light conditions. Remote Sensing 15 (19): 4890. DOI: https://doi.org/10.3390/rs15194890
Jin X., Jie L., Wang S., Qi H. J., Li S. W. 2018. Classifying wheat hyperspectral pixels of healthy heads and Fusarium head blight disease using a deep neural network in the wild field. Remote Sensing 10 (3): 395. DOI: https://doi.org/10.3390/rs10030395
Karpiński S., Szechyńska-Hebda M. 2023. Systemic acquired acclimation, network acquired acclimation and cellular light

memory in plants – Molecular, biochemical, and physiological mechanisms. Advances in Botanical Research 105: 277–310. DOI: https://doi.org/10.1016/bs.abr.2022.11.005

Khanal S., Fulton J., Shearer S. 2017. An overview of current and potential applications of thermal remote sensing in precision agriculture. Computers and Electronics in Agriculture 139: 22–32. DOI: https://doi.org/10.1016/j.compag.2017.05.001

Koshariya A., Sharma N., Satapathy S., Thilagam P., Laxman T., Rai S., Singh B. 2023. Safeguarding agriculture: a comprehensive review of plant protection strategies. International Journal of Environment and Climate Change 13 (11): 272–281. DOI: https://doi.org/10.9734/ijecc/2023/v13i113168

Lancashire P. D., Bleiholder H., van den Boom T., Langelüddeke P., Stauss R., Weber E., Witzenberger A. 1991. A uniform decimal code for growth stages of crops and weeds. Annals of Applied Biology 119: 561–601. DOI: https://doi.org/10.1111/j.1744-7348.1991.tb04895.x

Lowe A., Harrison N., French A. P. 2017. Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. Plant Methods 13 (1): 80. DOI: 10.1186/s13007-017-0233-z

Lu J., Hu J., Zhao G., Mei F., Zhang C. 2017. An in-field automatic wheat disease diagnosis system. Computers and Electronics in Agriculture 142: 369–379. DOI: https://doi.org/10.1016/j.compag.2017.09.012

Ma H., Huang W., Dong Y., Liu L., Guo A. 2021. Using UAV-based hyperspectral imagery to detect winter wheat Fusarium Head Blight. Remote Sensing 13 (15): 3024. DOI: https://doi.org/10.3390/rs13153024

Mahlein A. K., Oerke E. C., Steiner U., Dehne H. W. 2012. Recent advances in sensing plant diseases for precision crop protection. European Journal of Plant Pathology 133 (1): 197–209. DOI: https://doi.org/10.1007/s10658-011-9878-z

Mahlein A. K., Rumpf T., Welke P., Dehne H. W., Plümer L., Steiner U., Oerke E. C. 2013. Development of spectral indices for detecting and identifying plant diseases. Remote Sensing of Environment 128: 21–30. DOI: https://doi.org/10.1016/j.rse.2012.09.019

Mahlein A.-K., Kuska M.T., Behmann J., Polder G., Walter A. 2018. Hyperspectral sensors and imaging technologies in phytopathology: State of the art. Annual Review of Phytopathology 56: 535–558. DOI: https://doi.org/10.1146/annurev-phyto-080417-050100

Monteiro A., Santos S., Gonçalves P. 2021. Precision agriculture for crop and livestock farming – brief review. Animals MDPI 11 (8): 2345. DOI: https://doi.org/10.3390/ani11082345

Mostafalou S., Abdollahi M. 2017. Pesticides and human chronic diseases: Evidences, mechanisms, and perspectives. Toxicology and Applied Pharmacology 324: 94–104. DOI: 10.1016/j.taap.2013.01.025

Moustaka J., Moustakas M. 2023. Early-stage detection of biotic and abiotic stress on plants by chlorophyll fluorescence imaging analysis. Biosensors 13 (8): 796. DOI: https://doi.org/10.3390/bios13080796

Nguyen C., Sagan V., Maimaitiyiming M., Maimaitijiang M., Bhadra S., Kwasniewski M. T. 2021. Early detection of plant viral disease using hyperspectral imaging and deep learning. Sensors 21 (3): 742. DOI: https://doi.org/10.3390/s21030742

Pasternak M., Pawłuszek-Filipiak K. 2022. the evaluation of spectral vegetation indexes and redundancy reduction on the accuracy of crop type detection. Applied Sciences 12 (10): 5067. DOI: https://doi.org/10.3390/app12105067

Pena J.M., Torres-Sanchez J., de Castro A.I., Kelly M., Lopez-Granados F. 2013. Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images. PLoS ONE 8 (7): e77151. DOI: https://doi.org/10.1371/journal.pone.0077151

Poobalasubramanian M., Park E., Faqeerzada M., Kim T., Kim M., Baek I., Cho B. 2022. Identification of early heat and water stress in strawberry plants using chlorophyll-fluorescence indices extracted via hyperspectral images. Sensors (Basel, Switzerland) 22: 8706. DOI: https://doi.org/10.3390/s22228706

Qiu R., Yang C., Moghimi A., Zhang M., Steffenson B.J., Hirsch C.D. 2019. Detection of Fusarium Head Blight in wheat using a deep neural network and color imaging. Remote Sensing 11 (22): 2658. DOI: 10.3390/rs11222658

Roberts M. 2021. Spot spraying on target to cut inputs. Future Farming. [Available on: https://www.futurefarming.com/crop-solutions/weed-pest-control/spot-spraying-on-target-to-cut-inputs/] [Accession: November 11, 2021]

Sajid H. 2023. AI development lifecycle: Complete breakdown in 2023. Artificial Intelligence. [Available on: https://www.unite.ai/ai-development-lifecycle-complete-breakdown-in-2023/] [Accession: April 23, 2023]

Saleem M., Khanchi S., Potgieter J., Arif K. 2020. Image-based plant disease identification by deep learning meta-architectures. Plants 9 (11): 1451. DOI: https://doi.org/10.3390/plants9111451

Savary S., Willocquet L., Pethybridge S. J., Esker P., McRoberts N., Nelson A. 2019. The global burden of pathogens and pests on major food crops. Nature Ecology & Evolution 3 (3): 430–439. DOI: https://doi.org/10.1038/s41559-018-0793-y

Singh V., Sharma N., Singh S. 2020. A review of imaging techniques for plant disease detection. Artificial Intelligence in Agriculture 4: 229–242. DOI: https://doi.org/10.1016/j.aiia.2020.10.002

Szechyńska-Hebda M., Lewandowska M., Witoń D., Fichman Y., Mittler R., Karpiński S. M. 2022. Aboveground plant-to-plant electrical signaling mediates network acquired acclimation. The Plant Cell 34 (8): 3047–3065. DOI: https://doi.org/10.1093/plcell/koac150

Szechyńska-Hebda M., Wąsek I., Gołębiowska-Pikania G., Dubas E., Żur I., Wędzony M. 2015. Photosynthesis-dependent physiological and genetic crosstalk between cold acclimation and cold-induced resistance to fungal pathogens in triticale (*Triticosecale* Wittm.). Journal of Plant Physiology 177: 30–43. DOI: 10.1016/j.jplph.2014.12.017

Szechyńska-Hebda M., Wędzony M., Tyrka M., Gołębiowska G., Chrupek M., Czyczyło-Mysza I., Dubas E., Zur I., Golemiec E. 2011. Identifying QTLs for cold-induced resistance to *Microdochium nivale* in winter triticale. Plant Genetic Resources 9 (2): 296–299. DOI: https://doi.org/10.1017/S1479262111000268

Thenkabail P. S., Smith R. B., De Pauw E. 2000. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. Remote Sensing of Environment 71 (2): 158–182. DOI: https://dx.doi.org/10.1016/S0034-4257(99)00067-X

Tona E., Calcante A., Oberti R. 2018. The profitability of precision spraying on specialty crops: a technical-economic analysis of protection equipment at increasing technological levels. Precision Agriculture 19: 606–629. DOI: https://doi.org/10.1007/s11119-017-9543-4

Wan L., Li H., Li C., Wang A., Yang Y., Wang P. 2022. Hyperspectral sensing of plant diseases: principle and methods. Agronomy 12: 1451. DOI: https://doi.org/10.3390/agronomy12061451.

Wąsek I., Dyda M., Gołębiowska G., Tyrka M., Rapacz M., Szechyńska-Hebda M., Wędzony M. 2022. Quantitative trait loci and candidate genes associated with freezing tolerance of winter triticale (× *Triticosecale* Wittmack). Journal of Applied Genetics 63 (1):15–33. DOI: 10.1007/s13353-021-00660-1

Wielkopolska Izba Rolnicza. 2024. Calculation of production costs for winter wheat. [Available on: https://wir.org.pl/asp/start,0] [Accession: June, 2024] (in Polish)

Zaka M.M., Samat A. 2024. Advances in remote sensing and machine learning methods for invasive plants study: a comprehensive review. Remote Sensing 16 (20): 3781. DOI: https://doi.org/10.3390/rs16203781

Zanin A., Neves D., Pereira L., Ribeiro T., da Silva C., da Silva S., Teodoro P., Rojo Baio T. 2022. Reduction of pesticide application via real-time precision spraying. Scientific Reports 12: 563. DOI: https://doi.org/10.1038/s41598-022-09607-w
Zhang C., Kovacs J.M. 2012. The application of small unmanned aerial systems for precision agriculture: A review. Precision Agriculture 13 (6): 693–712. DOI: https://doi.org/10.1007/s11119-012-9274-5
Zhelezova S., Pakholkova E., Veller V., Voronov M., Stepanova E., Zhelezova A., Sonyushkin A., Zhuk T., Glinushkin A. 2023. Hyperspectral non-imaging measurements and perceptron neural network for pre-harvesting assessment of damage degree caused by Septoria/Stagonospora Blotch Diseases of wheat. Agronomy 13 (4): 1045. DOI: https://doi.org/10.3390/agronomy13041045