machines

MDPI

Viewpoint

Sustainable Crop Protection via Robotics and Artificial Intelligence Solutions

Vasiliki Balaska [1,*], Zoe Adamidou [2], Zisis Vryzas [2] and Antonios Gasteratos [1]

[1] Department of Production and Management Engineering, Democritus University of Thrace, 671 32 Xanthi, Greece; agaster@pme.duth.gr
[2] Department of Agricultural Development, Democritus University of Thrace, 691 00 Komotini, Greece; zoiadamidoy@gmail.com (Z.A.); zvryzas@agro.duth.gr (Z.V.)
* Correspondence: vbalaska@pme.duth.gr

Abstract: Agriculture 5.0 refers to the next phase of agricultural development, building upon the previous digital revolution in the agrarian sector and aiming to transform the agricultural industry to be smarter, more effective, and ecologically conscious. Farming processes have already started becoming more efficient due to the development of digital technologies, including big data, artificial intelligence (AI), robotics, the Internet of Things (IoT), and virtual and augmented reality. Farmers can make the most of the resources at their disposal thanks to this data-driven approach, allowing them to effectively cultivate and sustain crops on arable land. The European Union (EU) aims to make food systems fair, healthy, and environmentally sustainable through the Green Deal and its farm-to-fork, soil, and biodiversity strategies, zero pollution action plan, and upcoming sustainable use of pesticides regulation. Many of the historical synthetic pesticides are not currently registered in the EU market. In addition, the continuous use of a limited number of active ingredients with the same mode of action scales up pests/pathogens/weed resistance potential. Increasing plant protection challenges as well as having fewer chemical pesticides to apply require innovation and smart solutions for crop production. Biopesticides tend to pose fewer risks to human health and the environment, their efficacy depends on various factors that cannot be controlled through traditional application strategies. This paper aims to disclose the contribution of robotic systems in Agriculture 5.0 ecosystems, highlighting both the challenges and limitations of this technology. Specifically, this work documents current threats to agriculture (climate change, invasive pests, diseases, and costs) and how robotics and AI can act as countermeasures to deal with such threats. Finally, specific case studies and the application of intelligent robotic systems to them are analyzed, and the architecture for our intelligent decision system is proposed.

Keywords: Agriculture 5.0; green deal; pesticides; crop protection; Unmanned Aerial Vehicles; smart farming and harvesting; AI-based systems

Citation: Balaska, V.; Adamidou, Z.; Vryzas, Z.; Gasteratos, A. Sustainable Crop Protection via Robotics and Artificial Intelligence Solutions. *Machines* **2023**, *11*, 774. https://doi.org/10.3390/machines11080774

Academic Editor: Jiangjian Xiao

Received: 16 June 2023
Revised: 17 July 2023
Accepted: 21 July 2023
Published: 25 July 2023

1. Introduction

Agriculture 5.0 constitutes an entire ecosystem; it aims to integrate emerging technologies, such as AI, IoT, and ML in agriculture, to improve productivity while promoting sustainability and decision-making processes. Enhancing traditional farming practices through automation and scalable technology solutions is meant to reduce risks, enhance sustainability, and provide predictive decision-making for growers [1,2]. Moreover, data-driven agriculture and advanced farm management systems are becoming increasingly important in the contemporary agrarian sector. Smart agriculture relies on objective information acquired through sensors to make optimal decisions and maximize productivity while ensuring resource efficiency and environmental sustainability. By incorporating robotic solutions and AI techniques, data-driven agriculture lays the groundwork for sustainable agriculture in the future. In relation to Industry 5.0 (which emphasizes collaboration between humans and intelligent machines, with a focus on resilience and sustainability), Agriculture 5.0 seeks to reconcile the need for sufficient and affordable food production with the preservation of ecosystems. While Industry and Agriculture 4.0 focus mainly on technologies, like IoT and Big Data, Industry and Agriculture 5.0 add human, environmental, and social aspects to the equation. The transition from the digital farming revolution to Agriculture 5.0 is considered critical for the future well-being of farmers and the gradual shift to efficient, intelligent, and autonomous farms in terms of energy consumption. Integrating emerging technologies and alternative energy sources into Agriculture 5.0 can provide cost-effective access to finance, weather updates, remote monitoring, and future energy solutions for smart farm installations.

According to the European Agricultural Industry (EU-27), the growing demands on agricultural products as well as the growing world population have raised the demand for an increased production yield. Note that agriculture possesses strong links with food processing and farm machinery sectors. The latter is directly affected by the performance of the agrarian sector; thus, the total economic impact of agriculture is multiplied [3]. More specifically, the global population increase and the consecutive exponential one in food demand have led to a search for more efficient ways of production, both in terms of production size and quality of products. Specifically, the above reasons caused the Third Agricultural Revolution to flourish by introducing vital technological pillars in the agricultural field. The mentioned stations are: (i) the selective breeding to improve the quality of food in products for humans and animals as well as (ii) the use of chemical fertilizers and synthetic pesticides for increased quality production with a low environmental footprint. Chemical pesticides used to protect crops from pests, pathogens, and weeds pose acute and long-term risks to humans and other non-target organisms [4]. Moreover, many pesticides and their degradation products persist in the environment for many years [5]. The farm-to-fork, soil, and biodiversity strategies, as well as the zero pollution action plan, include ambitious and specific targets on pesticides, fertilizers, biological agriculture, and resistance development against pesticides (https://ec.europa.eu/info/food-farming-fisheries/sustainability/environmental-sustainability/cap-andenvironment_en (accessed on 1 April 2023)) [6]. Some clear targets to be achieved by 2030 are to reduce chemicals and more hazardous pesticides by 50%, reduce fertilizer use by 20%, and enhance the organic farming sector by 25% of total farmland (https://ec.europa.eu/info/food-farming-fisheries/farming/organic-farming/organic-production-and-products_en (accessed on 1 April 2023)). New technological advances must be introduced in traditional agricultural systems to support those EU targets. Hence, process automation can be a modern way of handling this situation. The high-tech precision agriculture systems result from the research and development of interdisciplinary teams in mechatronics and agronomy [7]. In this context, various vehicles have been developed, which are capable of moving in difficult rural terrains, while the development of drones has given new impetus to several applications, such as crop health assessment, plant monitoring, etc. These developments allow modern mechatronic systems to collect data, communicate wirelessly, and share large sizes of data between them [8,9]. The above data constitute a cornerstone of precision farming since they can be used for timely and accurate spraying of fungicides, insecticides and herbicides, fruit harvesting when appropriate for ripening, etc. This enables intelligent cultivation, production automation, and production automation, saving farmers' time in various stages of production, such as sowing, spraying, harvesting, etc. At the same time, farmers have the ability to control their processes and results through communication technology [10]. The evolution of modern robots has an impact on improving the quality of crops by increasing both the profitability of producers as well as the choice-consumption of quality food [11]. Therefore, the implementation of new technologies helps to restrict dosing and dispersal, thereby reducing the environmental consequences. However, independent of their targeted operational environment, contemporary robots should be smart and, thus, retain advanced perception abilities [12,13]. These capabilities are highly related to how the robots understand, interpret, and represent their environment and its elements (such as crops, leaves, etc.), and each individual productive entity (e.g., plants, trees, pests, pathogens, etc.). Semantic mapping is salutary and can provide viable solutions to related problems [14]. Also, the heterogeneous data extracted from an integrated system are necessary to be understandable and useful for the direct actions of the producers/farmers or for the direct supply to another robot system that implements the next action (for example, spraying, collecting fruit, etc.). The above challenges involve system advancements in terms of dependability and semantic perception abilities with the ultimate requirement of being operable in different environments.

Crop protection constitutes a major food production component. Using cutting-edge technologies such as the introduction of low-risk pesticides, precision farming, and genome editing will help to keep modern agriculture sustainable. Timely monitoring of crop protection problems and targeted application of the fit-for-purpose pesticide would reduce the overall risk and increase the efficacy of each application. Specifically, our proposed system will contribute to improving crop protection by making it more efficient and robust. The main contributions of our work are summarized as follows:

- To summarize the most recent and relevant literature in the domain of smart farming through robots.
- To highlight and stress the benefits of introducing an autonomous robotic ecosystem in the agricultural field.
- To reveal the technological challenges and barriers to introducing such solutions in this domain.
- To propose a conceptual framework for the realization of robotized systems in agricultural environments to help with their protection.
- To explore potential improvements in pesticide efficacy by providing timely pesticide delivery to targets.
- To investigate strategies for reducing the risk posed by pesticide applications to non-target organisms.
- To discuss the development of a decision support system for selecting low-risk pesticides among the available options.

The rest of this paper is structured as follows. Firstly, the crop justification is analyzed in Section 2. In Section 3, we discuss related works in the field of precision agriculture. In the same section, the problem formulation is also presented. Section 4 describes the agriculture field requirements, and the next section highlights the benefits of utilizing AI methods. In Section 5, we analyze the proposed system and its architecture. In Section 6, a discussion of our findings is provided, while in Section 7, our conclusions are drawn and plans for future work are presented.

2. Crop Justification

Two important crops for the EU economy were selected as case studies. A field crop (wheat) and a perennial crop (olive) constitute our models, covering different (i) cropping systems, (ii) pest/weed/pathogen severity, and (iii) registered pesticides. The olive tree (*Olea europea* L.) is a universal tree that has accompanied Mediterranean agriculture for thousands of years. Nowadays, over 750 million olive trees are cultivated worldwide, 95% of which are in the Mediterranean region. The fruit, oil, and branches of olive trees have been culturally and economically tightly linked with Mediterranean history (https://agriculture.ec.europa.eu/news/producing-69-worlds-production-eu-largest-producer-olive-oil-2020-02-04_en (accessed on 20 April 2023)). About 98% of olive oil and 80% of table olive production are from Mediterranean countries. Approximately 70% of the world's olive oil production is concentrated in Europe. In the EU, olive tree plantations are found in nine EU Member States: Spain, Italy, Greece, Portugal, Cyprus, France, Croatia, Slovenia, and Malta. EU olive production reached 10,908,000 tonnes and EUR 2255 million in 2016 [15]. The average annual olive yield and product quality varied between years, reflecting the effect of plant protection problems. The olive tree is a long-living drought-tolerant species that is limited by many biotic stressors (e.g., pests, diseases, and weeds). *Bactrocera oleae*, *Prays oleae*, *Euphyllura* spp., *Saissetia oleae*, *Parlatoria oleae,* and *Eriophyidae mites* are the most important pests and *Cycloconium oleaginum, Glomerella cingulata, Pseudomonas syringae pv. savastanoi* are among the diseases receiving chemical control by various pesticides. In the EU, olive cultivation tends to move from traditional low-density systems to new, high-density, super-intensive cropping systems. All of these changes have affected the incidence and severity of pests and diseases. In olive trees, at least ten of the currently registered pesticides, one insecticide (lambda-Cyhalothrin), seven fungicides (Bordeaux mixture, copper hydroxide, copper oxide, copper oxychloride, Difenoconazole, Tebuconazole, Tribasic copper sulfate), and two herbicides (Diflufenican, Metribuzin) are listed as candidates for substitution. Copper products are used in high quantities and most alternatives lack copper efficacy. Moreover, the limited number of pesticides registered for use in olives has resulted in resistance development to most pests, diseases, and weeds against insecticides, fungicides, and herbicides, respectively. Table 1 summarizes the currently registered pesticides in olive trees. Cereal grains have numerous uses, such as bread, semolina, and pasta; they are also important components of animal feed and serve as raw material in the production of products such as alcohol, beer, starch, and dextrin, and are used in the glucose industry. In the EU, the cereal sector accounted for approximately 11% of the total output value of agricultural production in 2016 and it is an important sector in the northern member states (https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/640143/EPRS_BRI(2019)640143_EN.pdf (accessed on 1 April 2023)). The EU cereal sector is facing structural, financial, and climatic challenges. Russia's war against Ukraine has put global food security at risk and has contributed significantly to the growing wheat and wheat flour prices. Around one-third of the EU's cereal imports in 2021 came from Ukraine and Russia; following the war, the EU had to undertake all measures to certify EU cereal production. Wheat, the most important cereal crop cultivated worldwide, is used to prepare bread for approximately 40% of the global population [16]. Wheat is an important commodity in Europe, with a production of 133 million tonnes per year. Wheat production depends on numerous production factors, and the use of pesticides is important for increasing the quantity and quality of wheat production. Pesticides help to control pests and diseases or their vectors, as well as reduce spoilage during storage. Broadleaf and grassy weeds, diseases (*Puccinia striiformis/graminis/recondita, Erysiphe graminis, Septoria tritici/nodorum, Fusarium* spp. *Tilletia caries, Ustilago nuda, Ustilago* spp., *Rhizoctonia* spp.), insects (*Agrotis* spp., *Rhopalosiphum padi, Sitobion avenae, Limothrips cerealium*), and other pests can reduce wheat crop yields, and the use of pesticides helps to minimize these losses. In the early stages of crop development, using herbicides to control weed infestations is essential for achieving optimal grain yield and desired economic benefits. With wheat, at least two insecticides (Cypermethrin, lambda-Cyhalothrin), one fungicide (Tebuconazole), and two herbicides (Pendimethalin, Metsulfuron-methyl) from the current authorized products are listed as candidates for substitution. Wheat production is also threatened by the development of weed resistance against most registered herbicides, and there are numerous instances of insects and fungi developing resistance against insecticides and fungicides, respectively. While the investigation into less harmful compounds to substitute undesirable pesticides is an important strategy, other promising smart farming technologies (innovative formulations), tools (innovative spraying equipment), and methodologies (lower dosages) can contribute to increased pesticide efficacy and reduced impact on the environment and human health. Table 2 summarizes the currently registered pesticides in wheat. AI can help in the selection of the most appropriate pesticides in order to achieve the highest efficiency against targeted crop protection problems and the lowest risks for resistance development and hazards related to non-target organisms. The mode of action of pesticides, the life cycle and susceptibility of pests/pathogens/weeds, stability, leaching and runoff potential, environmental conditions, and availability of application technologies are among the major factors that an AI system can be trained to handle.

Table 1. Major plant protection problems and the use of pesticides registered as conventional, low-risk, and candidates for substitution (C for S) in the cultivation of olive trees.

Crop/pests/pathogens/weeds	Olives/Bactrocera oleae, Prays oleae, Euphyllura spp., Saissetia oleae, Parlatoria oleae, Eriophyidae, Cycloconium oleaginum, Glomerella cingulata/broadleaf and grassy weeds Conyza spp. Parietaria Judaica
Registered insecticides and related plant protection products	Abamectin, acetamiprid, aluminium silicate, Bacillus thuringiensis (ABTS, SA1, PB5, EG2,GC-91), Beauveria bassiana, cyantraniliprole, deltamethrin, fatty acid potassium salt, fenoxycarb, flupyradifurone, paraffin oil, pyriproxyfen, spinetoram, spinosad, spirotetramat, hydrolyzed proteins, urea
C for S Insecticides	lambda-Cyhalothrin
Registered fungicides	azoxystrobin, Bacillus amyloliquefaciens, dodine, eugenol, fenbuconazole, geraniol, kresoxim-methyl, potassium phosphonates, pyraclostrobin, sulfur, thymol, Trichoderma asperellum, Trichoderma atroviride, Trichoderma gamsii, trifloxystrobin
C for S Fungicides	Bordeaux mixture, copper hydroxide, copper oxide, copper oxychloride, tribasic copper sulfate, difenoconazole, tebuconazole
Registered Herbicides	2,4-D, flazasulfuron, florasulam, fluazifop-p-butyl, fluroxypyr, flumioxazin, glyphosate, iodosulfuron, mcpa, mefenpyr, oxyfluorfen, pelargonic acid, penoxsulam pyraflufen-ethyl, tribenuron
C for S Herbicides	Diflufenican, metribuzin

Crop = olives Pests = Bactrocera oleae, Prays oleae, Euphyllura spp., Saissetia oleae, Parlatoria oleae, Eriophyidae. Pathogens = Cycloconium oleaginum, Glomerella cingulata. Weeds = broadleaf and grassy weeds Conyza spp. Parietaria Judaica.

Table 2. Major plant protection problems and registered conventional, low-risk, and candidate for substitution (C for S) pesticides in wheat.

Crop/pests/pathogens/weeds	Wheat/Agrotis spp./ Rhopalosiphum padi, Sitobion avenae, Limothrips cerealium/Puccinia striiformis, graminis, recondita, Erysiphe graminis, Septoria tritici, nodorum/broadleaf and grassy weeds
Registered Insecticides and related plant protection products	Deltamethrin, Fatty acid potassium salt, flonicamid, flupyradifurone, tau-fluvalinate, tefluthrin
C for S Insecticides	Cypermethrin, lambda-cyhalothrin, cypermethrin
Registered Fungicides	Azoxystrobin, benzovindiflupyr, bixafen, cyproconazole, difenoconazole, fenpicoxamid, fenpropidin, fludioxonil, flutriafol, fluxapyroxad, ipconazole, isopyrazam, mefentrifluconazole, prochloraz, prothioconazole, pyraclostrobin, sedaxane, spiroxamine, sulfur, trifloxystrobin
C for S Fungicides	Tebuconazole
Registered Herbicides	2,4-D, bentazone, carfentrazone-ethyl, florasulam, glyphosate, iodosulfuron, MCPA, mecoprop-p, mefenpyr, mesosulfuron, prosulfocarb, thiencarbazone-methyl, tribenuron
C for S Herbicides	Pendimethalin, metsulfuron-methyl

Crop = wheat Pests = Agrotis spp., Rhopalosiphum padi, Sitobion avenae, Limothrips cerealium. Pathogens = Puccinia striiformis, graminis, recondita, Rysiphe graminis, Septoria tritici, nodorum Weeds = Broadleaf and grassy weeds.

3. Related Works

This section presents the existing knowledge related to the research topic and provides an overview of the relevant literature. The purpose of this section is to contextualize the research of the field's current state. Through a comprehensive review of related works, gaps in the research can be identified, providing a rationale for our study. This section also allows readers to situate the research within a broader scholarly conversation and provides a foundation for the argument presented in the paper.

The importance of crop area (CA) protection can be attributed to the growing population. Automatic mapping using information extracted from high-spatial resolution remote sensing (RS) images is powerful for acquiring accurate and up-to-date CA maps. RS image information extraction includes feature classification, which is a long-standing research issue in the RS community [13]. Emerging deep learning techniques, such as the deep semantic segmentation network technique, are effective methods to automatically discover relevant contextual features and obtain better image classification results [17]. More specifically, several studies have dealt with agricultural precision sectors, contributing to increased agricultural yields. Note that the authors of [18] applied transfer learning to domain adaptation—from the source domain to the plant domain—by using a major category in the plant domain. Category adaptation was performed from the major to minor categories within the plant domain. UAVs are immediately accessible tools for remote sensing scientists and farmers. In recent years, small commercial UAVs (<50 kg) [19] have been available for environmental and agricultural applications. Much of the research on precision agriculture for conservation has focused on strategically placing conservation areas to minimize runoff contaminants (e.g., sediment, nutrients, and pesticides) and, subsequently, increasing water quality [20]. The approach in [21] stated that spatial variability in soil, crops, and topographic characteristics, combined with temporal variability between seasons, could lead to variable annual yield patterns. The complexity of interactions between yield-limiting factors, such as soil nutrients and soil water, requires specialized statistical processing to quantify convenience and, thus, inform crop management practices. This study used multiple linear regression models, cubic regression, and neural propagation networks to predict performance.

Generally, the advent of AI and robotized solutions have revolutionized crop protection by offering advanced capabilities and precision in addressing agricultural challenges. These technologies enable automated monitoring, early detection of pests and diseases, targeted application of treatments, and efficient resource management, leading to increased crop yields and sustainable farming practices. Semantic recognition plays a crucial role in crop protection by enabling the identification and classification of pests, diseases, and other threats to agricultural crops [13,14]. Through advanced algorithms and machine learning techniques, semantic recognition systems can accurately analyze images, sensor data, and other inputs to provide timely and targeted interventions, leading to improved crop health and yield [22,23]. In recent years, different machine learning techniques have been implemented to achieve accurate yield prediction for different crops. The most successful techniques used support vector regression [24], M5-Prime regression trees [25], and *k*-nearest neighbor [26]. The authors created the spiking neural network (SNN) model for timely crop yield prediction. The above approach [27] introduces SNN as a promising technique for spatiotemporal data modeling and crop analysis prediction. Because deep learning techniques have the capability to extract feature maps from data for estimation, they can be expected to have less dependency on the input data. Even in rural areas where data acquisition is limited, deep learning can be expected to provide good crop yield estimation [28].

In [29], the obstacles faced in implementing smart agri-robotic solutions for global broadacre crop production were analyzed. The authors argued that the current strategies and technologies used in agri-robotics are insufficient to address the unique complexities associated with large-scale crop farming. They identify several key challenges, including the unpredictable nature of diverse broadacre crops, the necessity for adaptable robotic systems, and the intricate decision-making processes involved in crop management. To overcome these challenges effectively, the authors proposed fundamentally rethinking existing approaches and technologies, like machine learning, computer vision, and sensor networks, as essential components of smart agri-robotic solutions. Furthermore, the authors of [30] presented an in-depth analysis of the use of intelligent robot systems in the field of ecological agriculture. The paper emphasized the significance of adopting advanced technologies to address challenges related to pest control and promote sustainable farming practices. By integrating robotic platforms, sensors, imaging techniques, and artificial intelligence algorithms, the paper discussed how these technologies enable precise and targeted pest management strategies, reduce reliance on chemical pesticides, and minimize environmental impacts. The benefits of intelligent robot plant protection systems, such as improved efficiency, reduced labor requirements, and enhanced crop yield, are highlighted. The authors also acknowledge potential challenges in implementing these systems, including cost, scalability, and compatibility with existing agricultural practices.

Subsequently, the approach in [31] provides a comprehensive summary of the role and impact of robotics, IoT, and AI in automating the agricultural sector. The review explores various applications of these advanced technologies, including automated harvesting, precision agriculture, crop monitoring, livestock management, and smart irrigation systems. It highlights how the integration of robotics, IoT, and AI can enhance efficiency, productivity, and sustainability in farming practices. The paper also emphasizes the importance of incorporating data analytics and machine learning algorithms for intelligent decision-making in agriculture. Finally, it addresses the challenges associated with implementing these technologies, such as cost, scalability, interoperability, and data privacy.

Moreover, in [32], the authors presented a comprehensive overview of the integration of machine learning and emerging technologies in precision crop protection, specifically focusing on the transition towards Agriculture 5.0. Specifically, the paper explored the immense potential of these technologies to revolutionize farming practices, improve sustainability, and optimize crop protection strategies. By delving into various areas, such as machine learning algorithms, sensor technologies, remote sensing, IoT, and data analytics, the review examined how these technologies could be utilized to enhance crucial aspects of agriculture, including crop monitoring, pest detection, disease diagnosis, and targeted application of agrochemicals. The authors emphasized the significance of context-aware and data-driven decision-making to achieve precision crop protection in the evolving agricultural landscape. Then, it addressed pertinent issues, such as data quality, scalability, privacy concerns, and the need for interdisciplinary collaboration among researchers, farmers, and policymakers. By highlighting these challenges, this approach provides a holistic view of the potential barriers and considerations that need to be addressed for successful implementation.

4. Analysis of Agriculture Field Requirements

As the global population is projected to surpass 9 billion by 2050, the agricultural industry will have to satisfy the increasing demand for food. Pesticides will play a crucial role in ensuring high crop yields. Pesticides, according to the Food and Agriculture Organization (FAO), include substances of natural or synthetic chemicals or biological ingredients used to repel, destroy, or regulate pests and regulate plant growth. They help to protect seeds and crops from unwanted plants, insects, bacteria, fungi, and rodents, and come in various types, such as herbicides, insecticides, fungicides, rodenticides, and nematicides [33]. However, pesticides, herbicides, and chemicals have increased significantly in recent years to manage plant diseases and increase crop productivity. This increases crop quantity, but it often lowers the quality, pollutes the land and groundwater, and poses several health risks, causing nearly 300,000 deaths worldwide each year. Early-stage disease detection using IoT-based solutions that deploy various sensors can help reduce the use of harmful chemicals. AI techniques, such as vision-based techniques using image processing, machine learning, and deep learning algorithms, have also been proposed for disease detection automation [34].

In recent years, significant advances have been made in the use of deep learning (DL) approaches to build high-performance AI models for plant disease detection. Some lightweight convolutional neural network (CNN)-based methods show promise for use in IoT applications. Despite advancements in these vision-based methods, real-world detection of plant diseases remains challenging due to complex backgrounds and varying environmental conditions. Crop monitoring through aerial/drone-based surveillance can be an alternative solution, but robust and reliable vision-based techniques are required to work for various crops. Expert knowledge and thorough training are required to recognize early symptoms of plant diseases and take timely action to prevent further spread [35]. Plant diseases are classified into different categories, and visible symptoms are important in identifying diseases. Smart agriculture systems using AI methods for plant disease detection can be effective solutions to combat the problem of crop loss. There have been successful case studies in developing countries, but field disease diagnosis in real time is still difficult. Several models have been proposed to detect healthy and diseased leaves from various crops using CNN classification techniques, achieving high accuracy [36].

AI techniques for crop protection in agriculture have become increasingly prevalent in recent years, allowing for more efficient and accurate identification of pests, diseases, and soil deficiencies. AI sensors are now being utilized to identify and target weeds, with the appropriate herbicides then being applied to the specific area. In addition, integrating IoT sensors and supporting technologies, such as drones, geographic information systems (GISs), and other tools allow for real-time data monitoring, measurement, and storage. The aforementioned data can empower farmers by providing valuable insights into areas needing irrigation, fertilization, or pesticide treatment. This enables them to make well-informed decisions, effectively allocating resources and minimizing unnecessary expenses. Overall, incorporating AI techniques into agriculture use cases can lead to improved harvest quality, reduced herbicide usage, increased profits, and significant cost savings [35]. Precision weed management is an efficient tool to meet the EU targets for pesticide use reduction. In field crops, like wheat, weed control is crucial to any plant protection scheme. Most of the proposed commercial technologies and prototypes for precision weed control consist of three essential elements (i) sensors for weed/crop detection, (ii) decision algorithms regarding the type of herbicides that would be the most efficient, and (iii) a precise sprayer to deliver the appropriate dose of each herbicide to the targeted weed. Of the above-mentioned parts, inputs and validation of the decision algorithm are the most crucial for increasing the efficiency and reducing the risk of the applied herbicide [37]. Saving herbicides by applying AI techniques in wheat depends on the location, stage, and distribution of the weeds [38]. The accuracy of the detected weeds could reach up to about 99% [39]. Apart from weed management, scientific modeling has also been employed for forecasting in an IoT context involving fungal diseases in winter wheat [40]. The recent progress in AI and automation have been applied to a machine-learning-based classification approach to distinguish pests of tree crops, including the olive fruit fly (*Bactrocera oleae* [41]. In addition, online analytical processing models have been used to combine inputs in an integrated pest management scheme of olive tree crop protection [42].

5. Benefits of Utilizing AI Methods in Crop Protection

The integration of robotics and artificial intelligence (AI) into agriculture has revolutionized the way crops are grown and protected. While the title "Sustainable Crop Protection via Robotics and Artificial Intelligence Solutions" suggests a focus on pest control, it is crucial to recognize that AI and robotics can contribute to comprehensive crop protection strategies. By leveraging these technologies, we can enhance agricultural practices and ensure a sustainable future for food production. While our primary focus lies in crop protection, specifically in the realms of weed and disease management, it is essential to acknowledge the broader scope of whole crop protection and monitoring. In this section, we aim to provide a concise overview of these additional components and highlight the invaluable contribution of AI solutions to these areas.

Crop protection encompasses various factors beyond weeds and diseases that significantly impact crop health and yield. Elements such as climate conditions, nutrition optimization, cultural activities, and plant physiology play crucial roles in ensuring comprehensive crop protection strategies. By leveraging AI solutions, we can unlock new possibilities and advancements in each of these areas.

Climate adaptation and resilience: Climate change poses significant challenges to agricultural productivity. AI and robotics can play pivotal roles in adapting and mitigating climate-related risks. Advanced algorithms can process vast amounts of climatic data, helping farmers make informed decisions about planting times, water usage, and crop selection. Robotics equipped with environmental sensors can monitor weather conditions, soil moisture levels, and pest outbreaks, providing real-time data to optimize crop management. With AI-driven climate modeling, farmers can anticipate weather patterns, allowing for timely adjustments and minimizing crop losses [32].

Nutrition optimization: Achieving optimal crop nutrition is crucial for both yield and quality. AI and robotics can optimize nutrient management by analyzing soil composition, plant nutrient requirements, and growth patterns. Intelligent systems can monitor nutrient deficiencies or excesses, enabling precise application of fertilizers or other supplements. Additionally, robotics can automate tasks such as precision seeding, weeding, and nutrient delivery, minimizing waste and maximizing resource efficiency. By tailoring nutrition strategies to specific crop needs, AI and robotics contribute to sustainable agriculture while reducing environmental impacts [43].

Cultural Activities and Labor Optimization: Agriculture encompasses a range of cultural activities that are essential for successful crop production. AI and robotics can automate and streamline various tasks, reducing labor-intensive efforts and optimizing resource allocation. For example, robotic systems can perform time-consuming activities such as harvesting, pruning, and sorting with greater accuracy and efficiency. By automating repetitive tasks, farmers can focus on higher-value activities, such as crop planning, disease management, and market analysis. The integration of AI and robotics not only enhances productivity but also improves the quality of life for farmers, making agriculture a more attractive profession [44].

Enhancing plant physiology and health: Understanding plant physiology is vital for effective crop protection. AI can analyze large datasets on plant physiology, growth patterns, and disease symptoms, enabling early detection and intervention. By analyzing the relationships between plant traits and environmental conditions, AI can develop models to predict plant stress and disease susceptibility. Robots equipped with cameras and sensors can precisely monitor plant health, detecting signs of nutrient deficiencies, water stress, or pest damage. This data-driven approach allows for proactive management strategies, reducing the reliance on reactive measures and promoting sustainable plant health [32].

Furthermore, we outline some additional advantages of utilizing artificial intelligence (AI) methods in crop protection and agriculture as a whole. By enhancing precision agriculture, AI systems are improving the overall accuracy and quality of crop yields. Primarily, AI technology plays a role in detecting plant diseases, pests, and poor soil nutrition. Using AI-based sensors, weeds can be identified and targeted, and the appropriate herbicide can be applied in the area. Additionally, AI techniques allow for the collection of soil health data, fertilizer recommendations, weather monitoring, and tracking of the product's readiness [45]. Hence, farmers are empowered to make informed decisions throughout the crop-growing process. Precision agriculture is a technique that incorporates the most efficient soil management practices, variable rate technology, and optimal data management methods to help farmers enhance crop yields and minimize expenses. AI can offer real-time insights to farmers, allowing them to identify which areas require irrigation, fertilization, or pesticide treatment [46]. Additionally, innovative farming methods such as vertical agriculture can boost food production while minimizing resource usage. This approach reduces herbicide use, improves harvest quality, increases profits, and has significant cost savings. By employing IoT sensors and other supporting technologies, farmers can monitor, measure, and store field data on various metrics in real time. Combining AI-based farming tools with IoT devices and software quickly provides farmers with more accurate information. Having better data enables farmers to make more informed decisions, reducing the time and money spent on trial and error [47].

6. Proposed Framework

6.1. Background and Use Case Scenario

Crop protection is an essential aspect of modern agriculture, and the use of fungicides, insecticides, and herbicides is common. However, the indiscriminate use of chemicals can lead to environmental damage and harmful effects on human health. An AI- and robotics-based crop protection system can provide a sustainable and efficient solution to this problem. The objective of this conceptual scenario is to develop an AI- and robotics-based crop protection system that minimizes the use of chemicals, chooses the most appropriate pesticide, and improves crop yield. The proposed methodology—as an example case—is applied to the agricultural crops colorof wheat and olive trees based on the following assumptions: (i) Major plant protection problems (pests/weeds/pathogens) of the selected crops (wheat and olive tree) have been identified (Tables 1 and 2). (ii) Registered insecticides, fungicides, and herbicides have been categorized as conventional, low-risk, and candidates for substitution. It is also necessary to integrate the following: (iii) A decision support system regarding the selection of the most appropriate pesticide on an integrated pest management (IPM) system. (iv) Environmental factors affecting efficacy and the environmental fate of pesticides. (v) Legislation and other policy information. The proposed crop protection scheme can be applied to environmentally sensitive cases (e.g., near protected surface- and ground-water bodies, sensitive non-target organisms, like bees, earthworms, and beneficial microbes) or in cases of resistance to pesticides pests/pathogens/weeds.

6.2. Concept

The proposed concept incorporates a comprehensive and research-driven approach to revolutionize crop protection and enhance agricultural practices. A preliminary phase involves the creation of an extensive database that encompasses detailed information about various plant diseases, their corresponding pesticides, and the overall health status of plants. This database forms the foundation for accurately identifying the specific disease based on the symptoms exhibited by candidate plants. To ensure practical implementation, the system utilizes portable devices, such as smartphones or tablets, to provide farmers with images of diseased plants for disease recognition. In larger crop areas, a UAV equipped with visual sensors, capable of high or low-resolution imaging, can perform the disease- and pest-recognition process. Additionally, the system obtains georeferenced data on the examined plants, enabling the determination of potential disease spread to nearby crops within the area.

Moreover, the system goes beyond disease identification and extends its capabilities to identify weed species and distribute grassy and broadleaf weeds automatically. This information empowers the system to automatically employ AI to select the most appropriate herbicide. In the future, selective spraying techniques utilizing UAVs could be implemented, provided that technological feasibility is achieved. This exciting prospect has the potential to revolutionize crop protection practices. The system also incorporates information on insect populations obtained from digital traps or other monitoring systems. In the pesticide prioritization process, considerations regarding the pesticide risk to non-target organisms in wheat and olive agroecosystems can be considered. The system adapts to specific crop/pesticide combinations by incorporating pesticide cutoff criteria or dedicated authorization schemes aligned with national or regional legislation.

Furthermore, the proposed system is designed to seamlessly communicate with other components of Agriculture 5.0. These include automatic watering functions, autonomous spraying robots, weather sensors, and software for optimizing spraying schedules, harvesting, and other farming operations. By leveraging these interconnected components, the system aims to optimize farm protection, create a sustainable ecosystem, and foster a holistic approach to agriculture. The proposed framework is depicted in Figure 1, highlighting the systematic flowchart of the entire process. Its primary focus revolves around crop protection, which is continuously threatened by weeds, pests, and diseases. Building upon this pipeline, the aim is to establish a digital ecosystem, termed the industrial metaverse (IM) digital world, which is capable of recording the complete life cycles of agricultural crops. This digital ecosystem will gather extensive information about the rural environment by leveraging IoT, virtual reality (including augmented reality capabilities), cloud and edge computing, and other features of Industry 5.0 (Agriculture 5.0), as depicted in Figure 2.

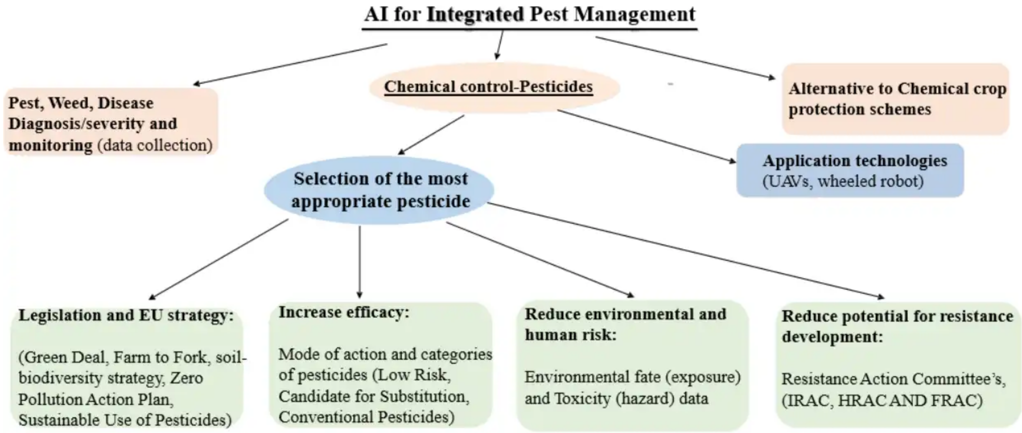

Figure 1. A flowchart of the crop protection system with AI and robotics techniques.

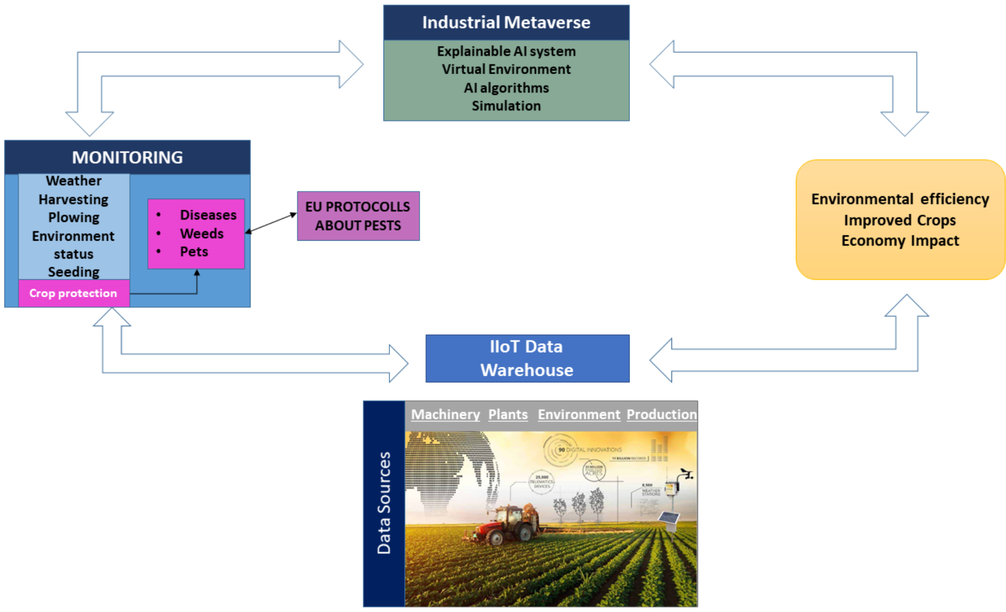

Figure 2. High-level architecture of a crop protection system with AI and robotics techniques.

Ultimately, the industrial metaverse comprises an explainable AI system that derives actionable results to improve production, environmental sustainability, and economic status. This comprehensive approach fosters communication across the supply-value chain, enhances responsiveness to potential issues, and improves safety, production efficiency, and environmental monitoring in real time. By leveraging the power of technology and research-driven methodologies, the proposed system aims to revolutionize agriculture and pave the way for a more sustainable and efficient future.

6.3. Architecture

The methodology of the above-described system for improving crop protection is based on extensive research and aims to provide a convincing and actionable solution. The proposed architecture encompasses various data collection techniques and advanced technologies, as illustrated in Figure 2. The agriculture field's digital transformation begins with IoT sensors for irrigation and weather monitoring. These sensors gather real-time data on soil moisture levels, temperature, humidity, and other relevant factors. Additionally, AI techniques are employed to recognize plant diseases based on visual cues and patterns, allowing for early detection and timely intervention. The production evolution aspect involves monitoring and analyzing crop growth and development over time.

The AI- and robotics-based crop protection system comprises several modules that work in tandem to enhance agricultural practices:

Data collection module: To generate valuable insights, the system collects data from diverse sources, including weather reports, soil sensors, satellite imagery, and digital insect traps. This comprehensive dataset enables accurate predictions of pest infestations, disease outbreaks, weed growth, and weather conditions.

Machine learning model development and interpretation module: This module involves the creation of automated systems that process data and derive meaningful conclusions. The system provides clear and actionable insights to guide decision-making by interpreting results from machine learning models.

Decision-making module: AI algorithms analyze the collected data and determine appropriate crop protection strategies. Factors considered include crop type, growth stage, severity of pests, weeds, or diseases, as well as environmental and risk assessment aspects related to pesticide use. Legislative limitations and the potential development of pesticide resistance are also taken into account.

Robot module: The system can be integrated into autonomous robots equipped with sensors, cameras, and spraying equipment. Through the use of machine learning algorithms, these robots are trained to accurately identify and target pests, weeds, and diseases, optimizing the effectiveness of crop protection strategies.

Monitoring module: AI is leveraged to monitor the effectiveness of crop protection strategies and make necessary adjustments in real time. This continuous monitoring ensures optimal performance and enables timely intervention when needed.

User interface module: To facilitate communication between farmers, agricultural scientists, and other stakeholders, a user interface is provided. This interface presents the system's findings and suggestions, allowing users to provide input and customize results according to their specific needs.

The above system will have the modularity and agility to integrate other modules, for example, blockchain and NFT development platforms, with the aim of achieving the traceability of foods. The AI- and robotics-based crop protection systems hold immense potential to revolutionize crop protection practices while minimizing the detrimental impact of chemical use on the environment and human health. The system maximizes crop yields and promotes sustainable agricultural practices by enabling farmers to make informed decisions about their crop protection strategies. However, implementing this system requires extensive research and development to continually improve its efficiency and effectiveness.

7. Discussion

Crop protection is a critical aspect of agriculture that involves safeguarding crops against various threats, including pests, diseases, and weeds. Traditional crop protection methods involve using fungicides, insecticides, and herbicides, which can adversely affect the environment and human health. However, with the advent of robotics and artificial intelligence (AI), farmers now have new tools at their disposal to improve crop protection and increase yields. Robotic- and AI-based crop protection solutions involve using sensors, cameras, and machine learning algorithms to monitor crops and detect potential threats. These solutions offer several advantages over traditional methods, such as increased accuracy, efficiency, and cost-effectiveness. For example, robots equipped with sensors can detect pest infestations and apply targeted treatments only where necessary, reducing the number of chemicals used and minimizing the environmental impact. Furthermore, AI algorithms can analyze vast amounts of data on weather patterns, soil conditions, and crop growth to predict potential threats and recommend preventive measures. This comprehensive approach enables farmers to make well-informed decisions regarding crop protection. It empowers them to effectively identify issues, choose the most suitable pesticide and application technology, and implement a reduced-risk crop protection scheme.

Robotic- and AI-based solutions for crop protection also offer the potential for increased precision and automation, reducing the labor costs and time required for manual inspection and treatment. For example, drones equipped with cameras and sensors can survey large areas of crops quickly and efficiently, providing real-time data on crop health and potential threats. In addition, robotic- and AI-based solutions can provide farmers with real-time insights into the health and growth of their crops, enabling them to make more informed decisions and optimize crop management practices. For example, machine learning algorithms can analyze data on crop growth and identify patterns and trends that may not be immediately apparent to human observers. Despite the many advantages of robotic- and AI-based solutions for crop protection, some challenges still need to be addressed. For example, these solutions may require significant investments in terms of hardware, software, and training. Additionally, there may be concerns about data privacy and security, particularly regarding sensitive information about crop yield and growth. In conclusion, robotic- and AI-based solutions have the potential to revolutionize crop protection and management, offering increased precision, efficiency, and cost-effectiveness. However, it will be essential to continue to develop these technologies and address any challenges to ensure that they are widely accessible to farmers and that they contribute to sustainable and ethical agriculture practices.

8. Conclusions

In conclusion, integrating robotic and artificial intelligence solutions into crop protection is a promising avenue for addressing modern agriculture's challenges. The potential advantages of these technologies include increased precision, efficiency, and cost-effectiveness, as well as better monitoring and management of crop health. Looking to the future, several research areas could further enhance the effectiveness of these solutions. For example, the development of more advanced sensors and cameras, as well as improvements in machine learning algorithms, could enable more precise and accurate monitoring of crop health and growth. Additionally, advances in robotics could allow for more sophisticated and automated treatment of crops, reducing the need for manual labor. Another important area of future work is the integration of these technologies with existing agricultural practices and infrastructure, including relevant legislation, risk assessment, and environmental aspects of AI modules. The availability of pesticide databases and alternative crop protection measures will help establish a robust machine learning model. This will require collaboration between farmers, agronomists, technology developers, and policymakers to ensure that the benefits of these solutions are accessible to all and contribute to sustainable and ethical agriculture practices. Finally, addressing data privacy and security concerns will be essential, particularly regarding sensitive crop yield and growth information. This will require the development of robust data protection and governance frameworks and greater awareness among farmers and other stakeholders about the risks and benefits of these technologies. Hence, the use of robotic and artificial intelligence solutions in crop protection has the potential to transform modern agriculture and ensure food security in the face of global challenges, such as climate change and population growth. Continued research and development in this area and integrating these technologies into existing agricultural practices will be crucial to realizing this potential and creating a more sustainable and resilient agricultural system for the future.

Author Contributions: Conceptualization, V.B., Z.A., Z.V. and A.G.; methodology, V.B. and Z.V.; validation, V.B., Z.A., Z.V. and A.G.; formal analysis, V.B., Z.A., Z.V.; investigation, V.B.; resources, A.G.; data curation, V.B.; writing—original draft preparation, V.B., Z.A. and Z.V.; writing—review and editing, A.G.; visualization, V.B.; supervision, A.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ahmad, L.; Nabi, F. *Agriculture 5.0: Artificial Intelligence, IoT and Machine Learning*; CRC Press: Boca Raton, FL, USA, 2021.
2. Ragazou, K.; Garefalakis, A.; Zafeiriou, E.; Passas, I. Agriculture 5.0: A new strategic management mode for a cut cost and an energy efficient agriculture sector. *Energies* **2022**, *15*, 3113. [CrossRef]
3. Chlingaryan, A.; Sukkarieh, S.; Whelan, B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Comput. Electron. Agric.* **2018**, *151*, 61–69. [CrossRef]
4. Larsen, A.E.; Patton, M.; Martin, E.A. High highs and low lows: Elucidating striking seasonal variability in pesticide use and its environmental implications. *Sci. Total Environ.* **2019**, *651*, 828–837. [CrossRef]
5. Parlakidis, P.; Rodriguez, M.S.; Gikas, G.D.; Alexoudis, C.; Perez-Rojas, G.; Perez-Villanueva, M.; Carrera, A.P.; Fernández-Cirelli, A.; Vryzas, Z. Occurrence of Banned and Currently Used Herbicides, in Groundwater of Northern Greece: A Human Health Risk Assessment Approach. *Int. J. Environ. Res. Public Health* **2022**, *19*, 8877. [CrossRef]
6. Schebesta, H.; Candel, J.J. Game-changing potential of the EU's Farm to Fork Strategy. *Nat. Food* **2020**, *1*, 586–588. [CrossRef]
7. Hensh, S.; Raheman, H. An unmanned wetland paddy seeder with mechatronic seed metering mechanism for precise seeding. *Comput. Electron. Agric.* **2022**, *203*, 107463. [CrossRef]
8. Nawar, S.; Corstanje, R.; Halcro, G.; Mulla, D.; Mouazen, A.M. Delineation of soil management zones for variable-rate fertilization: A review. *Adv. Agron.* **2017**, *143*, 175–245.
9. Tsolakis, N.; Gasteratos, A. Sensor-Driven Human-Robot Synergy: A Systems Engineering Approach. *Sensors* **2023**, *23*, 21. [CrossRef]
10. Fountas, S.; Aggelopoulou, K.; Gemtos, T.A. Precision agriculture: Crop management for improved productivity and reduced environmental impact or improved sustainability. In *Supply Chain Management for Sustainable Food Networks*; Wiley: Hoboken, NJ, USA, 2015; pp. 41–65.
11. Kim, N.; Lee, Y.W. Machine learning approaches to corn yield estimation using satellite images and climate data: A case of Iowa State. *J. Korean Soc. Surv. Geod. Photogramm. Cartogr.* **2016**, *34*, 383–390. [CrossRef]
12. Kostavelis, I.; Charalampous, K.; Gasteratos, A.; Tsotsos, J.K. Robot navigation via spatial and temporal coherent semantic maps. *Eng. Appl. Artif. Intell.* **2016**, *48*, 173–187. [CrossRef]
13. Balaska, V.; Bampis, L.; Kansizoglou, I.; Gasteratos, A. Enhancing satellite semantic maps with ground-level imagery. *Robot. Auton. Syst.* **2021**, *139*, 103760. [CrossRef]
14. Balaska, V.; Bampis, L.; Gasteratos, A. Graph-based semantic segmentation. In Proceedings of the International Conference on Robotics in Alpe-Adria Danube Region, Patras, Greece, 6–8 June 2018; pp. 572–579.
15. Torrecillas, C.; Martínez, C. Patterns of specialisation by country and sector in olive applications. *Technol. Soc.* **2022**, *70*, 102003. [CrossRef]
16. Giraldo, P.; Benavente, E.; Manzano-Agugliaro, F.; Gimenez, E. Worldwide research trends on wheat and barley: A bibliometric comparative analysis. *Agronomy* **2019**, *9*, 352. [CrossRef]
17. Sakurai, S.; Uchiyama, H.; Shimada, A.; Arita, D.; Taniguchi, R.I. Two-step Transfer Learning for Semantic Plant Segmentation. In Proceedings of the ICPRAM, Madeira, Portugal, 16–18 January 2018; pp. 332–339.
18. Li, Y.; Zhan, X.; Liu, S.; Lu, H.; Jiang, R.; Guo, W.; Chapman, S.; Ge, Y.; Solan, B.; Ding, Y.; et al. Self-supervised plant phenotyping by combining domain adaptation with 3D plant model simulations: Application to wheat leaf counting at seedling stage. *Plant Phenomics* **2023**, *5*, 0041. [CrossRef]
19. Lu, X.; Zhou, J.; Yang, R.; Yan, Z.; Lin, Y.; Jiao, J.; Liu, F. Automated Rice Phenology Stage Mapping Using UAV Images and Deep Learning. *Drones* **2023**, *7*, 83. [CrossRef]
20. Qin, C.; Wang, J.; Wang, H.; Xue, Q.; Niu, R.; Lu, L. Practice of the cross-scale and high-precision eco-environment zoning regulation—"Three lines and one permit". *Environ. Impact Assess. Rev.* **2023**, *101*, 107123. [CrossRef]
21. Jiang, G.; Grafton, M.; Pearson, D.; Bretherton, M.; Holmes, A. Integration of precision farming data and spatial statistical modelling to interpret field-scale maize productivity. *Agriculture* **2019**, *9*, 237. [CrossRef]
22. Balaska, V.; Bampis, L.; Katsavounis, S.; Gasteratos, A. Generating Graph-Inspired Descriptors by Merging Ground-Level and Satellite Data for Robot Localization. *Cybern. Syst.* **2022**, *54*, 697–715. [CrossRef]
23. Balaska, V.; Bampis, L.; Gasteratos, A. Self-localization based on terrestrial and satellite semantics. *Eng. Appl. Artif. Intell.* **2022**, *111*, 104824. [CrossRef]
24. Paul, R.K.; Das, T.; Yeasin, M. Ensemble of time series and machine learning model for forecasting volatility in agricultural prices. *Natl. Acad. Sci. Lett.* **2023**, *46*, 185–188. [CrossRef]
25. Kiruthiga, C.; Dharmarajan, K. Machine Learning in Soil Borne Diseases, Soil Data Analysis & Crop Yielding: A Review. In Proceedings of the 2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), Bengaluru, India, 27–28 January 2023; pp. 702–706.

26. Bandaia, K.; Gunasekaran, M. An Efficient Model for Predicting Future Price of Agricultural Commodities using K-Nearest Neighbors Algorithm Compared with Support Vector Machine Algorithm. In Proceedings of the 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 20–22 October 2022; pp. 858–861.
27. Jain, N.; Kumar, A.; Garud, S.; Pradhan, V.; Kulkarni, P. Crop selection method based on various environmental factors using machine learning. *Int. Res. J. Eng. Technol. IRJET* **2017**, *4*, 1530–1533.
28. Du, Z.; Yang, J.; Ou, C.; Zhang, T. Smallholder crop area mapped with a semantic segmentation deep learning method. *Remote Sens.* **2019**, *11*, 888. [CrossRef]
29. Grieve, B.D.; Duckett, T.; Collison, M.; Boyd, L.; West, J.; Yin, H.; Arvin, F.; Pearson, S. The challenges posed by global broadacre crops in delivering smart agri-robotic solutions: A fundamental rethink is required. *Glob. Food Secur.* **2019**, *23*, 116–124. [CrossRef]
30. An, Z.; Wang, C.; Raj, B.; Eswaran, S.; Raffik, R.; Debnath, S.; Rahin, S.A. Application of new technology of intelligent robot plant protection in ecological agriculture. *J. Food Qual.* **2022**, *2022*, 1257015. [CrossRef]
31. Krishnan, A.; Swarna, S.; Balasubramanya, H.S. Robotics, IoT, and AI in the automation of agricultural industry: A review. In Proceedings of the 2020 IEEE Bangalore Humanitarian Technology Conference (B-HTC), Vijiyapur, India, 8–10 October 2020; pp. 1–6.
32. Mesías-Ruiz, G.A.; Pérez-Ortiz, M.; Dorado, J.; de Castro, A.I.; Peña, J.M. Boosting precision crop protection towards Agriculture 5.0 via machine learning and emerging technologies: A contextual review. *Front. Plant Sci.* **2023**, *14*, 1143326. [CrossRef] [PubMed]
33. Thakur, P.S.; Khanna, P.; Sheorey, T.; Ojha, A. Trends in vision-based machine learning techniques for plant disease identification: A systematic review. *Expert Syst. Appl.* **2022**, *208*, 118117. [CrossRef]
34. Ryo, M. Explainable artificial intelligence and interpretable machine learning for agricultural data analysis. *Artif. Intell. Agric.* **2022**, *6*, 257–265.
35. Shruthi, U.; Nagaveni, V.; Raghavendra, B. A review on machine learning classification techniques for plant disease detection. In Proceedings of the 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), Coimbatore, India, 15–16 March 2019; pp. 281–284.
36. Kothari, J.D. Plant Disease Identification using Artificial Intelligence: Machine Learning Approach. *Int. J. Innov. Res. Comput. Commun. Eng.* **2018**, *7*, 11082–11085.
37. Rasmussen, J.; Nielsen, J.; Streibig, J.; Jensen, J.; Pedersen, K.; Olsen, S. Pre-harvest weed mapping of *Cirsium arvense* in wheat and barley with off-the-shelf UAVs. *Precis. Agric.* **2019**, *20*, 983–999. [CrossRef]
38. Zou, K.; Liao, Q.; Zhang, F.; Che, X.; Zhang, C. A segmentation network for smart weed management in wheat fields. *Comput. Electron. Agric.* **2022**, *202*, 107303. [CrossRef]
39. Gonzalez-de Soto, M.; Emmi, L.; Perez-Ruiz, M.; Aguera, J.; Gonzalez-de Santos, P. Autonomous systems for precise spraying–Evaluation of a robotised patch sprayer. *Biosyst. Eng.* **2016**, *146*, 165–182. [CrossRef]
40. El Jarroudi, M.; Kouadio, L.; El Jarroudi, M.; Junk, J.; Bock, C.; Diouf, A.A.; Delfosse, P. Improving fungal disease forecasts in winter wheat: A critical role of intra-day variations of meteorological conditions in the development of Septoria leaf blotch. *Field Crop. Res.* **2017**, *213*, 12–20. [CrossRef]
41. Tannous, M.; Stefanini, C.; Romano, D. A Deep-Learning-Based Detection Approach for the Identification of Insect Species of Economic Importance. *Insects* **2023**, *14*, 148. [CrossRef] [PubMed]
42. Zaza, C.; Bimonte, S.; Faccilongo, N.; La Sala, P.; Contò, F.; Gallo, C. A new decision-support system for the historical analysis of integrated pest management activities on olive crops based on climatic data. *Comput. Electron. Agric.* **2018**, *148*, 237–249. [CrossRef]
43. Rempelos, L.; Barański, M.; Sufar, E.K.; Gilroy, J.; Shotton, P.; Leifert, H.; Średnicka-Tober, D.; Hasanaliyeva, G.; Rosa, E.A.; Hajslova, J.; et al. Effect of climatic conditions, and agronomic practices used in organic and conventional crop production on yield and nutritional composition parameters in potato, cabbage, lettuce and onion; results from the long-term NFSC-trials. *Agronomy* **2023**, *13*, 1225. [CrossRef]
44. Khan, N.; Ray, R.L.; Sargani, G.R.; Ihtisham, M.; Khayyam, M.; Ismail, S. Current progress and future prospects of agriculture technology: Gateway to sustainable agriculture. *Sustainability* **2021**, *13*, 4883. [CrossRef]
45. Ghatrehsamani, S.; Jha, G.; Dutta, W.; Molaei, F.; Nazrul, F.; Fortin, M.; Bansal, S.; Debangshi, U.; Neupane, J. Artificial intelligence tools and techniques to combat herbicide resistant weeds—A review. *Sustainability* **2023**, *15*, 1843. [CrossRef]
46. Shaikh, T.A.; Rasool, T.; Lone, F.R. Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Comput. Electron. Agric.* **2022**, *198*, 107119. [CrossRef]
47. Wei, K.; Chen, B.; Zhang, J.; Fan, S.; Wu, K.; Liu, G.; Chen, D. Explainable deep learning study for leaf disease classification. *Agronomy* **2022**, *12*, 1035. [CrossRef]