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The Effectiveness of Using Artificial Intelligence in Agriculture: The Implications that Artificial Intelligence Can Have on Agriculture and Food Security

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Abstract

This research paper has focused on the application of artificial intelligence to enhance agricultural productivity and food security, by conducting a qualitative literature review of seven peer-reviewed articles published between the years 2016 - 2025 (Upadhyay et al., 2025; Agrawal & Arafat, 2024; Upadhyay et al., 2025; Mohanty et al., 2016; Ferentinos, 2018; Liakos et al., 2018). The study has investigated the use of machine learning, deep learning, computer vision and remote sensing technologies in regards to crop disease detection, precision farming and decision support systems. The results demonstrate that AI-based techniques are always better compared to the manual monitoring of crops for disease because they allow earlier diagnosis of crop stress and disease, making resources more efficient and minimise the loss of yield (Mohanty et al., 2016; Ferentinos, 2018). Additionally, the analysis has highlighted the crucial shortcomings of these AI-based techniques (Upadhyay et al., 2025; Majdalawieh et al., 2025). This included the use of controlled datasets, a lack of real-world validation and model-transparency. By analysing the cost-benefit aspect, this paper has stressed that although artificial intelligence has an immense potential in improving food security and sustainability, there is a need to apply more field tests, standardisation and following responsible use of artificial intelligence. This can be achieved to ensure that its application is more susceptible for a wider portion of the population.

Central Argument: AI can improve food security better than conventional measures.

Keywords: Artificial Intelligence; Digital Agriculture; Precision Agriculture; Machine Learning Applications; Food Security; Sustainable Agriculture; Agricultural Data Analytics; Computer Vision Farming; Deep Learning; Crop Disease Detection; UAV Drone Imaging; Remote Sensing; Soil Health Monitoring; Irrigation Management; Yield Prediction; Pest Detection; Early Disease Diagnosis; Sustainable Food Systems; Agricultural Robotics; AI Driven Supply Chain Management; Field-Based AI Testing

Introduction

The Current Issues with Agriculture and Food Safety: Why We Cannot Feed Ourselves Today

Agriculture is the backbone of human civilisation, growth and development, as it provides food and raw materials that are necessary for human survival. Despite the advancements that agriculture has made over the years, global agriculture faces numerous challenges that threaten food security (FAO, 2022; United Nations, 2021). For example: millions of people worldwide are undernourished. This is evident according to data from Food and Agriculture Organization (FAO), which pinpointed that between 713 million and 757 million people were undernourished worldwide in 2022. The figure increased by 152 million people between 2019 and 2023 (FAO, 2023). Most of the hunger issues are found in developing countries (FAO, 2022; World Bank, 2024).

What are the potential explanations for this challenge? Shouldn't subsistence challenges be well behind humanity? There are a number of challenges that people must tackle. For instance, we need to analyse the issues of climate change, soil erosion, over-tillage, deforestation, flooding, winds and water erosion, unstable population growth, having economic instabilities and lack of food security (FAO, 2022; IPCC, 2022; United Nations, 2021; World Bank, 2024). In the United States, industrial-scale livestock and crop farming can provide high productivity (USDA, 2022; FAO, 2022). In saying that, the US cannot escape concerns over food security. Productivity accounts for nearly 10% of national greenhouse gas emissions, mainly methane and nitrous oxide. Furthermore, according to the United Nations Environment Programme (2023), 33% of the world's soil is already degraded due to erosion, nutrient depletion and high chemical interference from intensive agriculture (IPCC, 2022).

Soil erosion is a major environmental issue that is affecting agriculture (FAO, 2023; IPCC, 2021). This natural process occurs when wind or water moves soil particles from one place to another. Factors, such as over-tillage, deforestation and flooding can heighten the problem. Over tillage means working the soil more than it needs. At first, it may help to control the weeds and prepare the land. However, repeated tilling can gradually harm the soil (FAO, 2023). It destroys soil structure, increases erosion and reduces the soil's ability to hold water and nutrients. Thus, making farming less sustainable over time. Soil erosion can result in diminished crop fields. In saying that, some measures could prevent the occurrence of soil erosion. This includes controlling the amount of water which is used for irrigation, utilising mulch and cover crops to protect it from winds and water erosion and preventing foraging of livestock. It is important to note that without consistent monitoring and planning, soil degradation continues to threaten sustainable agricultural production and food security (FAO, 2022; IPCC, 2021).

Additionally, the challenges from climate change include having unstable population growth and economic instabilities. These are known to worsen the situation in terms of agricultural production and food security (IPCC, 2022; FAO, 2023). In connection with climate change, a study conducted at PMC (2022) found that a 1% increase in greenhouse gas emissions correlated with a 1.39% increase in malnutrition prevalence in Sub-Saharan Africa (Shevchenko et al., 2023). In the OECD, FAO agricultural outlook from the years 2023 to 2032 in Sub-Saharan Africa is projected to have the highest population growth (OECD, 2023). This in turn would increase the pressure on its food systems. Other countries, such as The United States, Germany and France were also included to analyse trends in agricultural productivity, resource management and the adoption of AI technologies. Thus, making them directly relevant to the research context.

After the breakout of COVID-19 and the Ukraine war, global food prices have increased rapidly (FAO, 2024). These inflationary pressures could disproportionately affect low-income households, where food is a large part of the expenditures. On another note, traditional agricultural systems have struggled to balance having high production of food with sustainability. Thus, leaving food systems vulnerable to inefficiencies, having issues with resource storage and degradation of food. This is evident in China, as the overuse of nitrogen fertilisers has boosted short-term crop yields. However, they have led to a 20% to 30% decline in soil fertility and have caused major water pollution in the Northern China plain (FAO, 2023; IPCC, 2021).

On another level, several regions can fail to deliver productivity in agricultural development. There are a set of issues which are adding to this difficulty. Irrigation is a significant component of modern agriculture, and it has its own set of challenges. Although improved irrigation methods might increase crop yields and farmers income, problems for instance, limited monitoring of water use and soil conditions, can prevent them from applying water optimally. This can sometimes lead to overirrigation that wastes resources, or underirrigation which stresses the quality level of the crops. In regions that are prone to droughts, farmers heavily rely on groundwater. This can result in depletion of aquifers and long-term water scarcity. Inadequate infrastructures, such as outdated pumps and drainage systems, could further complicate water management and reduce overall farming productivity (FAO, 2023; World Bank, 2024).

A major issue that is threatening agricultural productivity currently is the limited access to high quality of the seeds. Besides the potential crop yield, high-quality seeds can guarantee their resistance against disease, insects and environmental stresses, such as drought or temperature. The use of genetically resistant seeds can improve food security through stable production even where stressful conditions apply. However, in various developing nations, high quality or genetically improved seeds remain unaffordable. Limited access could force many farmers to resort to using lower-quality or retained seeds. As a result, this decreases productivity and subjects crops to pests and shocks from the environment. The problem is further aggravated by weak seed distribution networks, subsidies or financial support. Thus, seed research and development investment are critical actions to give farmers access to seeds they need for food production that is sustainable and resilient (FAO, 2023; IMF, 2019).

Another persistent problem is the restricted availability and misuse of fertilisers and manures, and the overall impact that has on the health of crops. They supplement nutrients, such as nitrogen, phosphorus and potassium, that might otherwise be absent in the soil. Fertilisers can allow farmers to replenish depleted soils and gain higher returns, and manures improve soil structure and microbial well-being. Therefore, enabling continued fertility. Their inaccessibly high prices, unpredictable availability and transportation problems might discourage their applications from year to year. This is particularly in developing nations and remote agricultural regions. In addition, improper application or overuse of chemical fertilisers can lead to negative environmental effects. This includes water contamination, greenhouse gases and land degradation. Thus, solving these problems depends on better distribution systems and education in terms of following sustainable practices of nutrient management. This would enable farmers to be able to increase productivity without harming environmental health (FAO, 2023; IPCC, 2021).

Lastly, a significant challenge that is facing agriculture is the lack of access to modern farming equipment. Mechanisation can decrease the labour which is required for planting, harvesting and irrigation, so that farmers can treat more land with higher accuracy. Sophisticated equipment, such as tractors, combine harvesters and precision irrigation systems, could allow farmers to incorporate high-end farming techniques that can increase yield and sustainability. The application of such machinery is normally constrained in most developing nations since the equipment is costly, unavailable and/or not supplemented with adequate training. Without proper equipment, farmers are unable to execute time-sensitive interventions, optimise resource usage or increase output to counter increasing demand. Therefore, investment in equipment supply and being supported by training programs is essential in order to facilitate farmers, eradicate inefficiencies and promote sustainable agriculture development (FAO, 2024; McKinsey & Company, 2023).

In connection with tackling the issues, many people have turned to Artificial Intelligence to defeat the conventional challenges in agriculture (FAO, 2023; World Bank, 2024). These traditional issues include the late diagnosis of diseases in crops, poor utilisation of water and fertilisers, lack of capacity to have real-time monitoring of large farms and the use of manual decision-making processes (Liakos et al., 2018; FAO, 2023). These challenges can be specifically solved with the help of artificial intelligence. It can identify diseases in the early stages with the help of computer vision, increase the precision of irrigation and conduct nutrient management. With the help of data-driven models, large-scale surveillance alongside drones and satellite imagery, and automated decision support systems can enhance efficiency and minimise the loss of yields (Agrawal & Arafat, 2024; FAO, 2023; Liakos et al., 2018; World Bank, 2024).

The Significance of the Paper

Understanding the role of Artificial Intelligence in agriculture is important because the global food system is at a turning point. Rise in populations, environmental stress, soil degradation and unstable markets continue to strain the ability of farmers to produce a sufficient amount of food. Numerous traditional farming methods cannot match with these pressures, and countries that are facing hunger problems continue to remain vulnerable to the pressure. AI can offer tools which could improve decision-making, reduce waste and increase productivity in ways conventional practices cannot achieve alone (World Bank, 2024; FAO, 2023). It is essential to study this topic because the choices that people make today will lead to how food is grown, distributed and sustained for the future generations. If people use methods and AI effectively, farmers will be supported, the environment will be protected and food systems will be strengthened.

In agriculture, the major AI practices, such as computer vision, machine learning analysis and automated decision making, can complement each other. For example, computer vision decodes images that are taken by drones or satellites, machine learning analyses the measurements and automated tools can enact the recommendations. This integrated sensing-learning-prediction-action process means that AI progresses through a full cycle rather than performing one task on its own (Agrawal & Arafat, 2024; FAO, 2023). Sensing refers to the collection of data through drones, satellites and soil sensors. Learning indicates the machine learning models which use data to identify patterns or problems. Prediction involves forecasting outcomes, such as yield levels or potential pest outbreaks. Finally, action means the automated or farmer guided decisions that follow, such as adjusting irrigation, applying fertilisers or treating crops before damage spreads (Agrawal & Arafat, 2024; FAO, 2023). According to Microsoft FarmBeats program and the FAO report (2023) on digital agriculture, these methods are central to how AI operates in real agricultural environments.

Aims and Goals of the Paper

This research paper aims to explain how AI can work together with agriculture. It will analyse AI's benefits and limitations and analyse how it can improve food security in different regions. The goal is to highlight where AI can make a meaningful difference, what challenges still exist and why balanced adoption is necessary. Overall, the research argues that AI should be viewed as a tool that strengthens human efforts in farming and not replaces them. Thoughtful integration can help build a food system that is more productive, inclusive and resilient.

Literature Review

Understanding the Nature of Artificial Intelligence

Artificial intelligence or also known as AI, is revolutionising agriculture. This is because Artificial intelligence is capable of doing various tasks, such as analysing data, recognising patterns and making decisions. Unlike other databases, AI is not considered static. It is a technology that is capable of adapting to new information and learning from larger data sets. Artificial Intelligence can bring together different subdomains: each of which contributes to how it functions and how it influences companies in agriculture. This includes machine learning, deep learning, computer vision, natural language processing and robotics (Liakos et al., 2018; Upadhyay et al., 2025).

Machine learning can enable AI systems to make predictions by using observations in gigantic sets of data and identifying various patterns. Deep learning is a branch of machine learning. It utilises neural networks to map complex data, such as images or sound, which can be applied to disease detection in crops or livestock monitoring. On a similar level, computer vision enables AI to analyse satellite and drone images to assess the quality of soil, the health of plants and the efficiency of irrigation. Natural language processing allows for communication through translating verbal and written language. Thus, AI may be able to read farmers' reports or help farmers. Automation and robotics are transforming labor-intensive agricultural activities, such as planting, weeding and harvesting into being more efficient and less labour-intensive (Agrawal & Arafat, 2024; FAO, 2023; Liakos et al., 2018; Upadhyay et al., 2025).

AI is merging with agriculture as an essential tool for improving efficiency, sustainability and resilience (Chang, 2025). By providing the capacity to process and examine vast amounts of data, AI can allow farmers to make improved choices and optimise every step of food cultivation. For instance, AI-driven systems can examine soil nutrients, predict weather patterns and suggest precise irrigation schedules to conserve water (FAO, 2023). Similarly, predictive analytics can calculate harvest quantities. This could allow markets and governments to plan for probable shortages or surpluses. In addition, AI plays a critical role in supply chain management by forecasting demand, reducing spoilage and improving distribution systems (World Bank, 2025; FAO, 2023). With the increasing effects of climate change, AI simulations could help design adaptation strategies. Thus, ensuring long-term food stability and sustainable production.

To fully understand and appreciate AI's role in this context, firstly it is important to define agriculture and food security. Agriculture is the art and science of seed planting and animal production for food and other significant commodities, such as fruit, vegetables and grains. It is the pillar of human existence, binding economic progress, environmental protection and technological innovations together. Modern agriculture is no longer just about seeding and harvesting: it is also about soil health management, diversification and resource use efficiency. It encompasses numerous industries, such as crop production, animal husbandry, aquaculture, forestry and processing. Agriculture is reinforced with a complex network of inputs and infrastructure, such as seeds, fertilisers, irrigation systems and equipment (FAO, 2022 - 2023).

Additionally, the food system depends upon a diverse group of stakeholders who ensure that the process of food production and supply remains smooth. Farmers are at the forefront, as they are dealing directly with crops and animals. While input suppliers could provide the required inputs, such as fertilisers and machinery. Governments could develop policies and provide subsidies, researchers can develop innovative practices, and financial institutions might provide credit and insurance. NGOs and international organisations can assist small-scale farmers and promote sustainable practices. Lastly, consumers complete this loop, as their preferences and buying habits influence the production trends and sustainability goals (FAO, 2023; World Bank, 2024).

The Significance of Food Security

Food security is a crucial outcome of successful agricultural systems. It is a condition where all people at all times have physical, social and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life. It is built on four pillars: availability, access, utilisation and stability. Availability ensures that sufficient food is grown or brought in. Access provides that people have the physical and economic ability to access it. Utilisation is about nutrition and food safety. Lastly, stability ensures that these conditions persist over time. Food security can be reached when these components are in balance. Achieving food security is crucial for personal welfare and international stability, as it can impact economic growth, social cohesion and public health (FAO, 2022).

When threatened, food insecurity has consequences far beyond just hunger. Malnutrition, economic crisis and social unrest are impacts of the issue. The groups that are most affected are children, women and small-scale farmers. Economic output falls, inequality rises and ecosystems degrade due to unsustainable actions out of desperation. Therefore, addressing food security is essential to prevent widespread humanitarian and economic crises.

The Need for Using AI in Agriculture

Building agriculture with technologies, such as AI, is crucial in terms of making food systems stable and resilient. There are many pressures that are faced by the agriculture sector. By leveraging innovation and responsible utilisation of resources, AI could offer a pathway to a safer, necessary and more sustainable future for global agriculture. For instance, modern farms can generate enormous complex datasets from satellites, drones, soil sensors and weather stations. Farmers cannot hand-roll this amount of data at decision-making speed (World Bank, 2024; FAO, 2023). In line with this, reports that were summarised from the World Bank (2024) and FAO (2023) highlighted that digital tools are imperative for curating and analysing the streams of data. On another level, many regions struggle with degradation of their soil's water scarcity and increasing climate variability. According to the Intergovernmental Panel on Climate Change (IPCC, 2021) and global soil assessments (2022 - 2023), more than ⅓ of the world's soils exhibit some level of degradation. AI can help manage limited resources by identifying where water, fertiliser or pest treatments will have the greatest impact (FAO, 2023; IPCC, 2021; World Bank, 2024).

Furthermore, food systems need to be flexible and responsive to climate and price volatility. According to reports about food security that were issued by the FAO (2024), numerous areas of the world are being subject to abrupt disturbances which can be due to either weather extremes or triggered by market shocks. AI can provide rapid forecasts for pests, crop stress and yield outcomes to help stabilise production and minimise food losses.

The Process and Effectiveness of Using Artificial Intelligence in Agriculture

The general application process of AI in agriculture includes four stages (Liakos et al., 2018; FAO, 2023). This includes data collection, data interpretation, model training and prediction, and decision making or action. During the first stage, farmers begin by collecting data. This means that they would receive information from soil sensors, weather stations, drone photos, satellites and yield monitors (FAO, 2023; Liakos et al., 2018; Microsoft FarmBeats, 2017 - 2021). Microsoft's FarmBeats and FAO from 2017 to 2021, have expressed that without this step, farmers cannot achieve much progress with AI on the farm. Next as part of data interpretation, it is about making sense of all the data. Farmers need to decide what actually matters. This includes aspects, such as vegetation indices, soil moisture maps and crop health signals (NASA Earth Observatory, n.d.; European Space Agency, 2023; Microsoft FarmBeats, 2017–2021).

During the data interpretation phase, farmers can dwell on major indicators which facilitate extraction of useful data out of raw data. The most commonly used indices of vegetation include the Normalised Difference Vegetation Index (NDVI). This quantifies the amount of greenness and vitality of vegetation by using satellite or drone images. The importance of these indices is that the farmers can check the health of the crops covering vast land, and detect the stress easily in time due to nutrient deficiency, pests or drought (NASA Earth Observatory, n.d.; European Space Agency, 2023). On another level, the soil moisture map indicates the distribution of water in a field through the use of soil sensors and remote sensing technology. The data is necessary to optimise the irrigation process, avoid overwatering, save the water resources and sustain the crop production. Crop health signals are sensor and imagery based, and model based data that help identify early diseases, pest infestation or developmental abnormalities. These indicators are valuable as they allow farmers to act early with specific measures to reduce losses in yield, and limit the excessive applications of fertilisers and pesticides (Agrawal & Arafat, 2024; European Space Agency, 2023; FAO, 2023; Liakos et al., 2018; NASA Earth Observatory, n.d.; Upadhyay et al., 2025).

Machine learning reviews can clearly demonstrate the impact of how well the models work. Followed by this, the models can be trained and it can make predictions about crop yields, potential disease outbreaks, nutrient deficiencies, and irrigation needs. This can be achieved by observing past yields, outbreaks and weather. Machine learning could find patterns and begin forecasting about what would be the next step (Liakos et al., 2018; Upadhyay et al., 2025). Nature Scientific Reports (2025) have highlighted numerous evidence that these models can predict yields, or spot disease risks better than the traditional methods (Upadhyay et al., 2025; Upadhyay et al., 2025; Ferentinos, 2018). As a final step, farmers can place the predictions to work. That can include changing when they irrigate, adjusting fertiliser and/or aiming for pest control right where it is needed. Programs from the USDA (2020 - 2025) and NIFA (2025) highlight how sensors and automated irrigation systems can use these recommendations and apply them directly to the field.

Researchers have stressed that AI systems need regular updates with new data to stay current in the agriculture landscape. Other studies about using responsible AI have emphasised another idea: that if farmers want reliable results, they need transparency and local testing every step of the way. Artificial intelligence systems could track a wide range of parameters which can influence crop health and the outcomes of the yield. Some factors include soil moisture, nutrients level, pH level and other properties of soil that are measured by the soil monitor (FAO, 2023; USDA, 2022).

The soil moisture refers to the amount of water in the soil that is accessible to the roots of plants. It must be maintained at an optimal level where crops can get sufficient water without any form of waterlogging and root destruction. The soil nutrient levels could explain how the fundamental elements, including nitrogen, phosphorus and potassium are available and in right proportions. This can facilitate the growth of plants without high fertiliser application to the soil, which can cause environmental degradation. The content of soil pH level illustrates the extent to which the soil is acid or alkaline. For the majority of crops, the soil should have a pH level that is slightly acidic to neutral within a range of 6.0 to 7.0 to enable efficient uptake of nutrients. The rest of the soil properties, such as soil texture, soil temperature and the content of organic matter, can determine the water retention and the growth of the root activity of the microbes. Hence, they are essential in regards to long term soil health and productivity (FAO, 2023; NASA Earth Observatory, n.d.; European Space Agency, 2023; Liakos et al., 2018; Upadhyay et al., 2025).

USDA (2022) and NIFA (2024 - 2025) have underlined how these measurements can guide irrigation and fertilisation strategies. In addition, the vegetation of the region and the characteristics of the crops could be detected through AI monitoring. Satellite and drone images can provide information about vegetation indices, such as normalised difference vegetation index (NDVI), leaf chlorophyll levels, canopy cover and plant height. Microsoft FarmBeats (2017 - 2021) and remote sensing research have underlined that these measurements are essential for detecting stress early.

On another level, the quantity of the leaf chlorophyll level might demonstrate how much chlorophyll is present in the plant leaves, and it is more closely associated with nutrient status, particularly nitrogen. Furthermore, the leaf chlorophyll levels can enable the farmers to determine whether the crops are photosynthesising efficiently. Canopy cover could be described as the ratio of ground conservation of soil moisture. Lastly, plant height is a morphological measure of growth which indicates the overall development of the crop. It might be used to signify growth retardation due to water stress, nutrient deficiency or diseases (NASA Earth Observatory, n.d.; European Space Agency, 2023; Liakos et al., 2018; Agrawal & Arafat, 2024; Upadhyay et al., 2025).

The Impact of Weather

Weather plays a significant role in terms of how crops grow and how much stress they face. FAO (2021) and the World Bank (2025) have pinpointed that monitoring the weather is an essential aspect for managing resources. Aspects such as, rainfall, temperature, humidity and sunlight, can get tracked closely through the use of machine learning. Furthermore, AI can assist in regards to any issues in terms of pests and diseases (Mohanty et al., 2016; Ferentinos, 2018; Safarijalal et al., 2022). This includes detecting pests, such as aphids, spider mites, whiteflies and locusts. In addition, crop diseases for instance, powdery mildew, leaf rust, blight, bacterial leaf spot and late blight.

I tools allow farmers to react swiftly by identifying the visual patterns which are related to the pests and diseases. This is before they can spread and infest the farms and cause huge losses in yield. Computer vision can detect elements, such as yellowing leaves, strange spots and/or patterns in the canopy. It can provide farmers with early warning signs which they need in order to take care of the crops. Studies that have been conducted on image-based disease detection prove that noticing the problems early can reduce crop losses. Additionally, farmers' log details could ensure that the crops grow effectively and less wastage can occur. Some examples of log details include how densely they plant the crops and how much water they use (Mohanty et al., 2016; Ferentinos, 2018; Safarijalal et al., 2022; Upadhyay et al., 2025; Liakos et al., 2018; FAO, 2023).

The Role of Robotics

On the other level, robotics is another field where AI may be effectively applied to agriculture (FAO, 2023; USDA, 2020–2022; Agrawal & Arafat, 2024; El Alaoui et al., 2024). Sensors and computer vision tools that are installed on the systems can be used in weed, thinning and harvesting crops with high accuracy. According to reports by FAO (2021-2023) and USDA (2020-2022), these kinds of machines will reduce labor requirements and limit the damage to crops.

Additionally, AI can be used in supply chain management to predict demand, enhance storage efficiency which is based on monitoring of the environmental conditions and predict the waste of products (World Bank, 2025; FAO, 2023). The guidelines of the World Bank (2020 - 2022) about the use of digital food systems pinpoint that digital technologies can be used to reduce food loss, enhance supply chain coordination and stabilise prices. Lastly, climate forecasting with the use of AI may help regions to be prepared in cases of extreme weather conditions (IPCC, 2021 – 2022; Shevchenko et al., 2023; Science

Direct, 2025). For instance, drought, floods and heatwaves. The reports of the IPCC and responsible AI models stress that such simulations help farmers and policymakers make resilient decisions, such as climate-adaptive crop choices, and having better water management and planning in the long-term (IPCC, 2021; IPCC, 2022; Shevchenko et al., 2023; World Bank, 2025; Artificial Intelligence in Agriculture, 2025).

Methodology

This study has used a qualitative literature review research approach to examine the application of artificial intelligence and machine learning in the farming sector. This approach has been selected due to the possibility to compare and synthesise the results of a broad body of research instead of basing the results of one dataset or experiment. It is a highly suitable approach to new areas, such as artificial intelligence in agriculture where technology, models and applications can vary. The methodology allows defining the general trends, strengths, weaknesses and gaps in studies in current AI-related farming practices.

This is specifically in terms of crop disease, precision farming and remote sensing. Precision farming is defined as the application of data-driven technologies in order to optimise agricultural inputs. This includes water, fertilisers and pesticides (Liakos et al., 2018; Agrawal & Arafat, 2024).. Whereas, remote sensing is the gathering of crop and land information by using satellite, and UAV-based images to inform the state of the plant health and the environmental conditions (Agrawal & Arafat, 2024;NASA Earth Observatory, n.d.).

The academic research articles were gathered by using reliable academic sources, such as Google Scholar, SpringerLink, MDPI and the ScienceDirect (Upadhyay et al., 2025; Agrawal & Arafat, 2024; Science Direct, 2025). These databases were selected on the basis of accessing peer-reviewed journal articles and complete research papers that are highly utilised in academic research. To find the relevant studies, the following keywords were used: artificial intelligence in agriculture, deep learning plant disease detection, machine learning crop disease and UAV precision agriculture. The search was limited to the recent research which was conducted in the years 2024 - 2025, as it was considered that the information would reflect current developments in the field of AI in agriculture.

Inclusion and Exclusion Criteria

The inclusion criteria of the current study incorporated aspects such as, the articles have to be peer-reviewed, published in reputable academic journals and specifically discuss the applications of AI or machine learning in the agricultural industry. The selection criteria was restricted to only studies which provided a clear explanation of their research methodology and explained and evaluated practical applications of AI. This included detecting a disease, monitoring a crop and/or making decisions in farms.

Therefore, certain articles were not considered in the studies, as they were not directly connected to agriculture, did not apply AI or machine learning and/or were not methodologically detailed and accurate enough to include in this study. Additionally, the exclusion criteria incorporated articles that were purely opinion based and provided theory without any data collection and analysis. The papers were excluded as they were not adding meaningful and credible data to this paper.

1. **Deep Learning and Computer Vision in Plant Disease Detection: A Comprehensive Review of Techniques, Models, and Trends in Precision Agriculture by Upadhyay et al (2025), published in Springer**

The research paper addressed the increase in the role of deep learning and computer vision in regards to the identification of plant diseases through the analysis of images. The authors highlighted that there is a considerable benefit of AI-based image recognition technologies over the manual type of inspection. This was due to their capability to detect the diseases earlier and with the enhanced accuracy. This has been of great significance in the field of agriculture as infected crops are detected early. It can help to avoid loss of large volumes of crops and unnecessary use of significant amounts of chemicals.

To support this claim, the authors carried out a large-scaled systematic review of more than 270 studies that had been published before. They used a diverse set of deep learning architectures, such as the convolutional neural networks (CNNs), vision transformers and hybrid models as part of their methodology (Upadhyay et al., 2025; Mohanty et al., 2016; Ferentinos, 2018). Additionally, the review analysed the effect of varying image types, including RGB, multispectral, hyperspectral imagery and data set, training method and evaluation measure variations. The findings of numerous studies enabled the authors to find and pinpoint the general performance trends, without only using the results of the one experiment.

The findings revealed that deep learning models were able to attain high accuracy rates in terms of plant disease and early stress symptoms detection. This is especially with respect to large and heterogeneous datasets. The first benefit of this research method is that it is comprehensive in nature since the evidence used by the researcher incorporates various studies that are carried out to give an authoritative overview of the field. However, there are certain limitations that exist. This includes the fact that a significant part of the studies was carried out under controlled laboratory and not real-life farming conditions. The results might be made more accurate due to the application of it in the real world. Conducting field tests would have made the findings more accurate and credible. One of the critical research gaps which can be witnessed in the paper is the absence of the long-term validation and standardised benchmarks in terms of assessing the AI-based disease detection systems.

2. **Transforming Farming: A Review of AI-Powered UAV Technologies in Precision Agriculture by Agrawal and Arafat (2024), published in Drones by MDPI**

In this paper, the author has discussed the combination of artificial intelligence and unmanned aerial vehicles (UAVs) or drones in the application of precision agriculture. The main concept of the research paper was that the AI-driven UAVs were capable of enhancing crop surveillance considerably by providing high-resolution aerial images. This could identify the trend in terms of the health, diseases and variability of growth of the plants.

The research methodology used by the authors was a review. They studied a wide scope of literature where machine learning and deep learning algorithms were applied to UAV-gathered data. The researchers examined the aerial images in order to obtain vegetation indexes, canopy structure and signs of stress in extensive agricultural plots. Comparing various UAV systems, sensors and AI models allowed the authors to evaluate the effectiveness of drone-based systems in detecting crop stress and disease in comparison to the conventional ground-based surveillance techniques.

Vegetation indices are the numbers obtained as a result of aerial photographs quantifying the health of plants by the reflectance of light: greenness, photosynthetic activity. By studying the canopy structure, the authors discovered that UAV photos have the potential to correctly measure the density of plants, the canopy cover and the uniformity. These are significant parameters of crop development and yield potential. With regards to stress detection, the researchers found that the vegetation indices and canopy pattern change could frequently provide early warning of water stress, nutrient deficiency, or disease prior to the onset of its symptoms (Agrawal & Arafat, 2024; NASA Earth Observatory, n.d.; European Space Agency, 2023).

The results demonstrated that AI-controlled UAVs are suitable in terms of detecting crop stress and disease at an early stage, and surveying a wide area at low costs. The key benefit of this method is that it is possible to obtain repeated and high-resolution spatial data within a reasonably short period. The paper illustrated a number of limitations, such as high cost of operation, short battery life, regulatory and technical expertise. According to the authors, accuracy and usefulness might be enhanced through the combination of UAV data with ground-based sensors and the enhancement of image processing algorithms. A gap in the literature was that the analysis of UAV images is not standardised. Thus, the results cannot be compared between studies.

3. **Precision Agriculture in the Age of AI: A Systematic Review of Machine Learning Methods for Crop Disease Detection (2025), published in Artificial Intelligence Technology by ScienceDirect**

This paper has discussed a broad variety of machine learning and deep learning models in the detection of crop diseases and the assessment of plant health. The central argument of the article is that the current AI-related solutions are superior to previous disease detection algorithms, such as manual field inspections, especially in terms of their speed, scalability and accuracy.

In order to support this claim, the authors compiled their findings with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) systematic review framework. The PRISMA systematic review framework works by guiding researchers through a structured process of identifying, screening, assessing eligibility and incorporating studies that are based on predefined criteria (Majdalawieh et al., 2025). This provided transparency and consistency in the selection and analysis of the study. They searched and screened over 150 studies which they considered relevant based on the detection of crop diseases in various crops and regions. The approach applied by the research paper was comparison in regards to the types of models used, the size of the data sets, the performance measures and the practical applicability. The systematic nature meant that the authors could minimise the bias and enhance the validity of the findings.

The findings showed that deep learning models had higher accuracy rates than conventional machine learning methods particularly when trained on large and diverse data sets. One of the disadvantages of the study was that mostly it reviewed data by using small or area-focused databases. Therefore, this restricted the generalisability of findings. The authors propose that accuracy would be enhanced with the help of increasing datasets, trying models under different climates and using explainable AI methods. One research gap that is evident is that most AI models cannot be interpreted, and this may lower the levels of trust and acceptability amongst farmers and policymakers.

4. **Machine Learning in Agriculture: A Review by Liakos et al. (2018), published in Sensors by MDPI**

The paper provided an overall idea about the application of machine learning methods in various fields of agriculture, such as crop monitoring, disease detection, yield prediction and soil analysis. The primary claim of the research was that machine learning could be useful in enhancing decision-making in agriculture by processing huge amounts of data which can be gathered through sensors, satellites and farm equipment. To reinforce this argument, the authors conducted a systematic review of the available literature which implemented supervised and unsupervised learning models about agricultural data.

The process of this paper was to examine the applied methodologies of the various machine learning algorithms on different agricultural applications. This included support machines, random forests and neural networks. The authors compared the model performance in terms of accuracy, efficiency and scalability. Their results demonstrated that machine learning models worked best where large and high quality datasets can be obtained. This enables them to make more accurate predictions about crop health and yield results. The benefit of this study approach is that it gives a comprehensive picture of how machine learning approaches are applied in various agricultural areas, instead of just in one area.

The paper included a number of limitations. This incorporated the fact that a number of the sampled articles were based on small data samples, or on regional-specific circumstances. Thus, they cannot be considered as being generalisable. A gap in the study is that there is no real-time application and long-term validation of the field since most machine learning models are at an experimental level and cannot be immediately adopted in the farming sector.

5. **Deep Learning Models for Plant Disease Detection and Diagnosis by Ferentinos (2018), published by The Computers and Electronics in Agriculture**

The aim of the study was to investigate deep learning models, especially convolutional neural networks which are used to detect plant diseases using leaf images. The central argument of the paper was that deep learning models have high accuracy in regards to identifying plant diseases in cases where they are trained using large and well-labeled datasets of images. To substantiate this statement, the author has performed experimental testing using tens of thousands of images and various types of crops and diseases.

In this paper, the methodology applied included the training and testing of CNN architecture on a big amount of plant disease images collected under controlled conditions. The accuracy and classification measures were used to determine model performance. The findings demonstrated that deep learning models were highly effective relative to traditional machine learning techniques, and they had very high accuracy. The benefit of this research approach is that a large dataset was used. This increased the credibility of the results and proved the possibility of deep learning in the field of classifying the disease.

The limitations of the study included that the photos were mostly taken in controlled laboratory conditions. This means that it is possible that the models would be less effective in farm conditions. The author summarised that the accuracy might be enhanced through training models by using field images with changing lighting, backgrounds and current stages of the plant growth. A key gap identified in the study was the lack of testing in real agricultural settings. This is essential for practical deployment.

6. **Crop Disease Detection Using Deep Learning by Mohanty et al., (2016), published by the journal Frontiers in Plant Science**

The study focused on the use of deep learning to automatically detect plant diseases based on the digital images of crop leaves. The central argument of the article was that the deep learning models can be effectively used to separate healthy and diseased plants, without the need of human judgement by an expert. This is a great advancement compared to the old manual method of inspection, which is tedious and relies on the expertise of a specialist.

To prove this argument, the authors have referred to a large publicly accessible image dataset which was composed of thousands of labeled images in various crops and disease types (Mohanty et al., 2016; Ferentinos, 2018). Their aim was to have convolutional neural networks trained in order to classify pictures in terms of apparent symptoms of the disease. Various crops and types of diseases, such as wheat and tomato crops, which were affected by leaf rust and late blight were used to test the models to determine their ability to generalise. The findings demonstrated that deep learning models are highly accurate in classification. This is especially when they are trained by using large well-labeled datasets containing diverse images which are captured under different environmental conditions. The main benefit of this research approach was that it can be scaled to a large number of crops and diseases as the same model architecture can be used.

The paper’s limitations include that the majority of the images were taken in controlled conditions: the backgrounds were homogenous and there was sufficient lighting, which is not the case in the real world farm experiences. Consequently, the efficiency of these models might reduce in the application in real-world agriculture environments. According to the authors, accuracy might be enhanced with the help of field-based pictures and the inclusion of environmental information, including weather conditions. A gap that was observed in the research was the fact that there was no focus on the interpretability of models, and farmers had limited knowledge of how or why certain predictions of the disease were made.

Findings and Discussion

The research papers that were reviewed indicate that artificial intelligence and, specifically, the deep learning and computer vision innovations have a considerable positive effect on the accuracy and speed of plant disease detection. This is in comparison to the old manual inspection systems. In all seven articles, AI models that operated on images displayed high accuracy in terms of detecting disease symptoms at early stages when they are not always noticeable by the human eye (Upadhyay et al., 2025; Ferentinos, 2018; Mohanty et al., 2016). This implies that AI applications can be critically analysed as having massive prospects in improving early intervention, decreasing the loss of crops and increasing agricultural output. The data which is demonstrated in the studies enable us to learn that the data quality, the size of the dataset, and the environment where the data is gathered can be of great importance to the model performance (Upadhyay et al., 2025; Liakos et al., 2018). The higher accuracy and improved generalisation were reported in the studies that utilised large and diverse image datasets. Conversely, models which were trained on small or highly controlled datasets exhibited a lower level of reliability when used in the farming environment.

One of the obvious patterns that is evident throughout the papers is the correlation between the diversity of datasets and the robustness of models. Experiments involving pictures taken in actual field settings, UAV platforms, or in diverse geographic areas demonstrated better performance stability as compared to experiments based on laboratory or greenhouse data only. This suggests that environmental variability is one of the most important factors affecting the successful implementation of AI models in practice in the agricultural environment (Agrawal & Arafat, 2024; Safarijalal et al., 2022). The second similarity is that deep learning models, such as convolutional neural networks and vision transformers, perform better compared to the older machine learning models (Upadhyay et al., 2025; Majdalawieh et al., 2025). The performance difference is related to the fact that deep learning models are capable of automatically deriving complex features out of images. Whereas, the traditional models require features to be hand-engineered. Nevertheless, this power implies an additional cost of computations and the data demands, which were discussed as a major issue in various reports.

The variations were found between image analysis on the ground, UAV-based monitoring and satellite-driven methods. It was discovered that UAV-based systems were especially useful in surveying large farms and estimating spatial patterns of diseases. In contrast, ground-based imaging offered more detailed information on a plant level. The differences occur mainly because of the differences in the size of images, the image resolution and the process of acquiring the data. This means that no one system is purely best and hybrid systems can introduce the best solutions. Moreover, the studies varied in the evaluation metrics which were used to assess the models. Some used accuracy as the only measure and others used the precision, recall and F1-score. Therefore, the variations have an impact on the interpretation and comparison of performance in studies. Absence of standardised methods of evaluation can restrict direct comparison, and in other cases result in overestimation of model effectiveness (Majdalawieh et al., 2025).

The results verify the fact that AI-augmented disease detection systems can become an important element in precision agriculture as they will allow early diagnosis, specific treatment and fewer pesticides. The significance of such consequences is both economical and environmental in terms of saving the money and lowering the ecological burden to farmers. Furthermore, the findings indicate that the widespread use of AI technologies may lead to increased food security since it will reduce losses of yields due to plant diseases. Nevertheless, the outcomes pinpoint the issues of accessibility and scalability. Small-scale farmers might not have the same advantage of AI-driven solutions since it is expensive to implement, they might lack the technical knowledge and expertise, and have insufficient infrastructure. These problems should be addressed to provide an equal adoption of AI technologies in agriculture.

A key issue that is discovered in the findings is that there are small, non-standardised and publicly available datasets. Numerous articles used region or crop specific data, limiting the applicability of their results. In addition, it is a weakness of the present study since it relies on research, which is not necessarily representative of the diversity of agriculture in the world. The other weakness is the inexplicable AI models. Deep learning systems are highly accurate. However, their decision making is not always clear. This will decrease the confidence levels of farmers and other agricultural practitioners that might not trust the systems they do not have full knowledge about. To overcome this limitation, it would be helpful to improve model transparency.

The existing statistics indicate that the future of data in this area would have to use various sources of data, including the combination of image data with weather, soil, and sensor data. This multimodal practice is likely to enhance predictability and flexibility in all crops and climatic conditions. Moreover, the increase of the explainable AI focus and field testing stresses on the development of more pragmatic and user-friendly agricultural AI systems. According to the trends noted, it is plausible to believe that the AI-based approach to disease detection will keep advancing up to scalable, cost-efficient and field-ready solutions. Further development of research in the areas of diverse datasets, standardisation, and interpretability will be necessary in order to convert these technological breakthroughs into a broad agricultural usage.

Conclusion

This study has reviewed the recent scholarly literature about the application of artificial intelligence in agriculture. This incorporated crop monitoring, disease detection, precision farming and decision support systems. The results of all the analysed papers were coherent in terms of the claim that AI-based tools which rely on deep learning, computer vision, remote sensing and machine learning models can greatly enhance the process of early detection of crop stress, diseases and yield-related problems (Upadhyay et al., 2025; Agrawal & Arafat, 2024; Mohanty et al., 2016; Ferentinos, 2018; Liakos et al., 2018; Upadhyay et al., 2025). In contrast to the conventional methods of inspection conducted manually, AI systems are more precise, quicker in their reaction time and are efficient in regards to processing substantial amounts of data. These conclusions connect well with the main argument that artificial intelligence can be used to improve agricultural output and decrease the wastage of resources.

The results are a solid supplement of the hypothesis that AI-based agriculture can enhance decision-making and sustainability in agriculture. Combining the data of soil sensors, weather monitoring, drones and satellite images, AI systems can enable farmers to be proactive and not reactive to environmental and biological issues (Microsoft FarmBeats, 2017–2021; European Space Agency, 2023; NASA Earth Observatory, n.d.). On a larger scale, the study has explained the role that AI plays in enhancing food security across the world, by boosting the production of crops, losses related to pests and diseases, utilisation of water, fertilisers and labour. The point of the paper is that AI is not eliminating farmers. Instead, it is helping them with the evidence-based information to enhance the resilience and efficiency in agricultural systems.

It is important to know that these findings have enormous implications on policy and practice. Governments may adopt AI adoption by funding, infrastructural development and training, especially to the small-scale farmers and farmers in the developing region. These technologies can be used by the agricultural sector to minimise the effects on the environment by preventing over-irrigation and overuse of fertilisers (World Bank, 2025; FAO, 2023; IMF, 2019).

Future studies can focus on the validation of AI systems in actual farming conditions rather than controlled experiments. There are numerous studies which have been examined based on small datasets or region-based circumstances that limit external validity. The researchers in the future may examine the long-term performance of AI tools in various climates, soil types and types of crops. Another valuable direction is to create explainable AI models. This can enable farmers to have confidence and embrace it more by comprehending how the predictions and recommendations are obtained.

On the policy level, governments will be able to come up with the principles of responsible AI use in agriculture which will provide transparency, data privacy and access. Digital infrastructure implementation (including rural internet connectivity) is critical to a successful AI implementation as well. One related future research would be to examine the combination of AI and climate change adaptation plans, including the forecasting of droughts or extreme weather. The other potential question of research that can be conducted is how the adoption of AI varies between the large-scale commercial farms and the smallholder farms, and what can be done to close this technological disparity.

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