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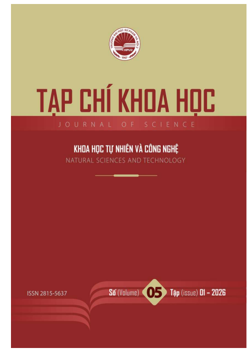

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Trends in applying artificial intelligence in agricultural cultivation and some orientations for Vietnam

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Abstract

This study examines the pivotal role of Artificial Intelligence (AI) in transforming agricultural biotechnology, especially amid the pressing challenges of climate change and the escalating global demand for food. AI has demonstrated considerable potential in optimizing agricultural processes through big data analytics, predictive modeling, and the development of novel crop varieties with enhanced resilience, improved resource efficiency, and reduced environmental impact. In precision agriculture, AI enables optimized use of water, fertilizers, and pesticides, and provides accurate forecasts for planting and harvesting schedules. Such capabilities substantially enhance productivity and mitigate production risks for farmers. AI applications for detecting pests and diseases have opened new ways to monitor and manage crops, thereby improving production quality and efficiency. AI also plays a key role in adapting agriculture to climate change, from smart irrigation management to adjusting farming practices based on weather conditions. However, for AI to reach its full potential in Vietnam, attention needs to be paid to factors such as digital infrastructure, training and awareness raising, cost and accessibility, integration with traditional methods, data security and adaptability to local conditions. These factors not only ensure effective AI deployment but also help bring sustainable benefits to Vietnam's agricultural sector in the digital age.

Keywords: Artificial intelligence, precision farming, climate change, object detection, disease detection, smart irrigation

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1. Introduction

In the context of deepening globalization and increasingly complex climate change, the agricultural sector is encountering profound challenges related to productivity, food security, and environmental protection [1], [2]. Abnormal weather patterns, the increasing frequency of extreme climate events, and the depletion of natural resources highlight the urgent need for advanced technological solutions that support both agricultural productivity and sustainability [3], [4]. Among recent innovations, artificial intelligence (AI) has emerged as a transformative tool capable of analyzing large datasets rapidly and accurately. This capability enables AI to deliver broad and effective solutions to many of the most critical challenges in agriculture. Using machine learning and deep learning algorithms, AI can process extensive data from diverse sources such as satellite imagery, soil sensors, and meteorological records. This analytical capacity enables AI to support optimal decision-making for crop planning, pest management, irrigation scheduling, and harvesting, thereby improving production efficiency while minimizing resource waste [5]. In agricultural biotechnology, AI has great potential to develop resilient crop varieties and optimize land and water use helping reduce environmental degradation. Furthermore, AI contributes substantially to climate adaptation strategies by forecasting and responding to climate-related risks. By analyzing climate models alongside real-time environmental data, AI can predict extreme weather events, enabling farmers to prepare and respond promptly to reduce losses and maintain productivity. For an agricultural nation like Vietnam, where the impacts of climate change are increasingly evident [3], [4], [6] integrating of AI into agricultural biotechnology not only enhances productivity and product quality but also supports the transition toward a sustainable, climate-resilient agricultural system.

However, implementing AI in agriculture in developing countries like Vietnam is not a simple task and requires careful preparation and assessment of many aspects. First of all, digital infrastructure in many rural areas of Vietnam is limited, including unstable internet connectivity, a lack of modern sensors, and incomplete digitization of agricultural databases. These factors can greatly hinder the collection, transmission, and processing of data, which are indispensable for AI to operate effectively in smart farming systems. In addition, the initial cost of implementing AI technology is a major barrier for many Vietnamese farmers, especially small-scale or household farmers. Investment in high-tech equipment, supporting infrastructure, as well as the cost of maintaining and updating the system, is often beyond their financial capacity. Therefore, there is a need for support policies from the state or for public-private partnership models to help reduce the cost burden and facilitate farmers' easy access to and use of AI. Human resource training is also an important factor that needs attention. Farmers and agricultural managers need basic knowledge of AI technology, as well as practical skills to operate and maintain AI systems effectively [1]. This not only helps them to maximize the benefits of AI but also enables them to be proactive in using and adjusting the technology to meet actual needs. In addition, data security poses a significant challenge when deploying AI in agriculture. Because AI relies heavily on data to make accurate decisions, data collection and processing must be conducted securely and transparently. This not only helps them maximize the benefits of AI but also allows them to take a proactive role in using and adjusting the technology to meet actual needs. Finally, the diversity of climate conditions, terrain, and farming practices in Vietnam also requires that AI solutions be flexibly customized to suit the specific characteristics of each region. For example, AI systems that perform well in the Mekong Delta with its tropical climate and complex irrigation network may not be suitable for the arid conditions and mountainous terrain of the Central Highlands. The development and adaptation of AI solutions must rest on a thorough understanding of local conditions. The active involvement of local experts and communities is also essential for the effective and sustainable application of these technologies in practice [2], [3].

The objective of this study is to explore and analyze trends in the application of AI in agricultural biotechnology and assess the potential and challenges of AI implementation in this field in Vietnam. The study focuses on clarifying how AI can be used to optimize farming processes and resource management, develop resilient crop varieties, and support adaptation to climate change. It also proposes specific solutions to promote the development of Vietnamese agriculture in a modern and sustainable direction. The study will also provide recommendations to improve the effectiveness of AI applications in agriculture by strengthening technical infrastructure, enhancing human resource training, ensuring data security and privacy, and ensuring adaptability to the specific conditions of each agricultural region in Vietnam.

2. Trends in artificial intelligence in agricultural cultivation

AI is a field of computer science concerned with creating systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and decision-making [4]. In agricultural biotechnology, AI has the potential to revolutionize the way we grow, manage, and maintain crops. AI can analyze large volumes of data from diverse sources, such as soil sensors, weather patterns, and genetic information, to optimize crop breeding programs, enhance disease and pest management, and improve resource use [5]. AI can be applied to predict crop performance, monitor crop health in real time, and tailor farming practices to specific environmental conditions. These applications help agricultural biotechnology achieve greater efficiency, sustainability, and resilience, thereby contributing to global food security and promoting the development of modern agriculture [7].

AI is increasingly important in agricultural biotechnology, especially in precision farming, climate change adaptation, phenotypic and genetic diversity assessment, soil health monitoring, sustainable farming, and environmental impact reduction. AI supports precision farming by analyzing sensor data, satellite imagery, and climate models to guide real-time management decisions. This approach can improve productivity while reducing the waste of agricultural resources [6]. In the context of climate change, AI supports the development of new crop varieties that are more drought-tolerant and more resilient to harsh environmental conditions. In addition, AI is applied to assess phenotypic and genetic diversity, supporting breeding improvement and biodiversity conservation. AI also enhances soil health monitoring and sustainable farming practices, thereby reducing negative environmental impacts and preserving natural resources. AI thus contributes not only to improving agricultural productivity but also to promoting sustainable development, adapting to ongoing global challenges.

2.1. Applications of artificial intelligence in precision farming

AI is making breakthroughs in precision farming, an advanced agricultural method that optimizes resource use and increases production efficiency. Precision farming relies on the collection and analysis of data from sources such as soil sensors, satellite imagery, and weather data, to inform farming decisions tailored to the specific conditions of each farming area. AI plays an important role in this process by processing large amounts of data, identifying patterns, and predicting environmental changes. These capabilities help farmers optimize farming practices and improve crop yields [7]–[9]. One of the main applications of AI in precision farming is optimizing the use of fertilizers, irrigation water, and pesticides. Instead of applying it uniformly across the entire field, AI can help farmers pinpoint which areas need more or less resources, based on real-time data on moisture, soil nutrients, and pest levels. This not only saves costs but also minimizes negative environmental impacts, such as water pollution and soil degradation. AI can also help predict optimal planting and harvesting times, based on weather forecasts and soil conditions. By analyzing data in real time, AI helps farmers make quick and accurate decisions, reducing the risks posed by climate change and unexpected factors. AI can also be integrated into smart farm management systems that enable farmers to monitor and control the entire farming process remotely and provide recommendations for improvement based on collected data. By applying AI in precision farming, farmers can not only improve the yield and quality of agricultural products but also build more sustainable farming systems. AI is ushering in a new era in agriculture, where precision, efficiency, and sustainability are key to meeting the world's growing food demand [10].

AI is playing an increasingly important role in the development of autonomous agricultural devices, especially in crop harvesting. These robots are equipped with computer vision and deep learning algorithms that enable them to accurately recognize and classify crops. By analyzing images and environmental data, the robots can determine the optimal harvest time to guarantee the highest product quality [11], [12]. This not only increases harvest efficiency but also minimizes waste and damage to agricultural products. Deep learning algorithms enable robots to learn and improve their recognition capabilities over time, which gradually enhances the harvesting process. AI also helps these robots process data from various sources, including sensors and cameras, to make accurate decisions even in changing environmental conditions. This is especially important in complex agricultural environments where small changes in temperature, humidity, or light can affect the harvesting process. Thanks to the combination of AI, computer vision, and deep learning, autonomous robots are not only capable of working continuously but can also outperform humans in many situations. They can harvest crops faster and with greater precision, minimizing human losses. At the same time, the application of this technology also helps reduce dependence on manual labor, optimize production costs, and increase the ability to meet global food demand. AI, with its power, is truly driving a revolution in agricultural harvesting, moving towards a more modern, efficient agriculture.

The first problem of AI application in precision farming is object detection. Object detection is a technology that uses AI algorithms, especially deep neural networks, to detect and recognize specific objects in images or videos. In precision farming, object detection is used to automatically identify crops, pests, weeds, and other environmental factors, helping farmers make accurate and timely farming decisions [13], [14]. One typical application of this problem in precision farming is crop health monitoring. By using images from unmanned aerial vehicles (UAVs) or sensors mounted on agricultural machinery, object detection can analyze images to determine the location and condition of individual crops in the field [15], [16]. A specific example of object detection in precision farming is weed detection for precision spraying using deep learning detectors such as YOLOv4 and Faster Region-Based Convolutional Neural Network (Faster R-CNN). In this application, red - green - blue (RGB) field images captured from ground platforms or UAVs are annotated with bounding boxes around weeds, and the model is trained to distinguish weed targets from crop plants and soil background at the object level rather than at the whole-image level [7]. This is agronomically important because weed populations are usually spatially patchy, so blanket herbicide application wastes chemicals and increases environmental exposure. In contrast, object-level detection allows herbicide to be directed only to infested zones [8]. A recent study evaluated the practical feasibility of spot spraying; performance was not assessed only by conventional metrics such as mean average precision (mAP) and inference speed, but also by task-specific indicators, including weed coverage rate (WCR) and area sprayed, because a detector with good mAP may still be unsuitable if it misses too many weeds at realistic nozzle widths [7]. That study showed that state-of-the-art vision methods could spray about 93% of weeds while treating only 30% of the field area, which illustrates why object detection has direct value for reducing herbicide use in precision agriculture. At the algorithmic level, cross-crop experiments with YOLOv4 and Faster R-CNN showed strong performance in the original cotton dataset, with AP values around 0.83 - 0.88 and mAP around 0.65 - 0.79. However, performance varied substantially when the same models were applied to soybean (*Glycine max*) and maize (*Zea mays*), where AP dropped as low as 0.33 in some settings. It shows that weed detection is not limited to architecture choice alone; it is strongly influenced by the training domain, crop background, weed morphology, image complexity, and annotation diversity [8]. Dataset design is also a key parameter [9]. For example, the Weed25 dataset contains 14,035 images of 25 weed species across different growth stages, and when identical training settings were used, YOLOv3, YOLOv5, and Faster R-CNN achieved average detection accuracies of 91.8%, 92.4%, and 92.15%, respectively [9]. These findings indicate that modern detectors can achieve high accuracy under controlled datasets. However, real field deployment still depends on robustness to occlusion, overlapping leaves, illumination changes, and transfer across crops and seasons. Therefore, weed detection should be interpreted not simply as an image-recognition success, but as a demanding object-detection problem in which model architecture, dataset scale, evaluation metric, and deployment context jointly determine whether AI can support reliable precision spraying in practice.

Next, the application of AI in disease detection is driving remarkable improvements in precision farming, helping farmers detect plant diseases early and manage them effectively. Disease detection uses AI algorithms, especially machine learning and deep learning, to analyze data from images, videos, or sensors to identify disease signs on leaves, stems, flowers, and fruits of crops [11], [12]. This technology allows farmers to monitor crop health in detail and accurately, thereby providing timely prevention and treatment measures, minimizing losses, and increasing productivity. An important application of AI in disease detection is the analysis of images from drones or sensors to detect crops abnormalities [16]–[18]. By using deep learning models, AI can identify symptoms such as leaf spots, yellowing, or rotting that are difficult to detect with the naked eye. This allows farmers to identify disease areas at an early stage and implement specific control measures, such as spraying pesticides precisely where needed, rather than the entire field. This not only saves costs and resources but also protects the environment from the negative effects of chemicals. Furthermore, AI in disease detection can learn and improve over time. AI systems can be trained on data from a variety of crops and conditions, increasing the accuracy of predictions and analysis. In addition, AI can combine multiple data sources, from satellite imagery, soil sensors, and weather forecasts, to provide early warnings of potential disease outbreaks. A representative application of AI in disease detection is image-based leaf disease identification using deep learning models such as CNNs and YOLOv8 [19]. In this approach, RGB images of crop leaves are used to train a detector that identifies diseased tissue and classifies the corresponding disease category at the same time, which is more informative than whole-image classification because it provides spatially explicit symptom localization. This application has strong agronomic value because early disease symptoms are often subtle, unevenly distributed, and easily confused with abiotic stress, nutrient deficiency, or mechanical injury. In contrast, object detection can support earlier and more targeted intervention in the field [19]. In particular, YOLOv8 achieved a mAP of about 98% and an F1 score of about 97%, which indicates strong detection performance on the curated dataset used in that study [19]. However, high accuracy under controlled image conditions does not necessarily mean that the model will remain robust under field environments with variable illumination, complex backgrounds, leaf overlap, mixed symptom severity, and large differences among cultivars and growth stages. It has been noted that plant disease detection performance depends strongly on dataset composition, annotation quality, symptom variability, and deployment context, and that many models still face limitations in generalization, interpretability, and real-time field application. Therefore, the significance of AI in disease detection lies not only in high predictive accuracy, but also in its capacity to integrate visual diagnosis with practical crop protection decisions, while acknowledging that reliable deployment requires broader validation across crops, seasons, and production environments.

The application of AI in pest detection is becoming an important tool in precision farming, helping farmers manage and control pests effectively and promptly. Pest detection uses AI algorithms, especially machine learning and computer vision, to analyze data from images, videos, or sensors to detect the pests on crops [15], [20]–[23]. This technology enables early pest detection and supports timely management decisions that reduce crop damage and protect yield. Artificial intelligence algorithms can analyze field images to identify the presence of pests, including insects, spider mites, and mealybugs, even when infestation levels remain low. This capability is agronomically important because early infestation is often difficult to recognize through routine visual inspection, particularly in large-scale production systems. Accurate early detection enables farmers to apply targeted control measures only in affected areas, rather than treating the entire field. Such an approach can reduce pesticide use, lower production costs, and lessen negative environmental effects. In addition, artificial intelligence can support the prediction of pest development and spread by analysing of environmental variables such as temperature, humidity, and soil conditions. By learning from historical records and current field data, these systems can identify conditions associated with pest outbreaks and provide early warnings before serious damage occurs. This predictive function is particularly important under climate change, where unstable weather patterns may alter pest dynamics and increase the likelihood of unexpected infestations.

Developing AI technology based on computer vision requires a complex learning (training) process, which involves collecting and photographing many samples in natural and dynamic environments to accurately reflect the conditions under which the equipment will operate. The performance of a deep learning system typically improves as the amount of high-quality data increases, allowing the system to overcome imaging problems such as lighting conditions, incorrect alignment, and incorrect cropping. These AI algorithms and technologies can be integrated with mobile hardware to create a platform that can cost-effectively detect and locate pests and diseases, and create prescription maps (compatible with precision farming equipment) for variable application of agrochemicals. Using these technologies, pesticide applicators will be able to apply the right amount of pesticide only where needed, reducing pesticide use and costs while minimizing potential environmental impact. These technologies could also be used to develop precise and cost-effective mechanical harvesting or pruning technologies for fruit and vegetable crops. More research is needed to develop low-cost and efficient AI-based systems for precision agriculture applications.

2.2. Applications of artificial intelligence in climate change adaptation

AI is becoming an important tool for supporting agricultural adaptation to climate change. Its value lies in its ability to process large and diverse datasets and convert them into information that supports more informed agricultural decision-making. This capacity helps farmers and agricultural managers optimize cultivation practices and reduce production risks as environmental conditions change. In the context of climate change, where weather patterns have become more unstable and difficult to predict, artificial intelligence can improve the analysis of climate and weather trends and support earlier responses to adverse events such as drought, flooding, and prolonged heat stress. These functions are important because they strengthen preparedness and improve the ability of agricultural systems' ability to respond to environmental uncertainty. One prominent application of AI in climate-adaptive farming is crop management. AI can help identify and develop crop varieties that are drought-, salt-, or high-temperature-tolerant, ensuring that farmers can maintain productivity even in harsh conditions. In addition, AI assists in optimizing resources such as water and fertilizers, helping reduce waste and protect the environment.

For example, AI systems can analyze soil sensors data and weather forecasts to recommend appropriate irrigation water, minimizing the risk of drought or water waste [24]. Furthermore, AI plays an important role in developing sustainable farming models, helping agriculture not only adapt to climate change but also mitigate its impacts. AI-based technologies can analyze the agricultural supply chain, from production to consumption, to find ways to save energy and reduce carbon emissions. A prominent example of AI in climate-adaptive crop management is irrigation scheduling based on reference evapotranspiration prediction using models such as Long Short-Term Memory (LSTM) networks and Particle Swarm Optimization–Long Short-Term Memory (PSO-LSTM) [25]. In this application, the model uses climatic variables, including air temperature, relative humidity, wind speed, and solar radiation, to estimate daily reference evapotranspiration (ET_o), which is a key parameter for determining crop water demand under changing weather conditions. This application is highly relevant to climate adaptation because rising temperatures, irregular rainfall, and prolonged dry periods make conventional irrigation schedules less reliable. It reported that PSO-LSTM models trained on long-term meteorological records improved ET_o prediction accuracy over standard methods, which indicates that artificial intelligence can support more precise irrigation decisions under variable climatic conditions. Specifically, the value of this approach lies in its ability to capture nonlinear relationships among weather variables that strongly influence crop water requirements, whereas fixed empirical schedules often fail to respond adequately to short-term climate fluctuations [25]. The agronomic implication is that farmers can adjust irrigation timing and amount more effectively, thereby conserving water, reducing drought stress, and stabilizing crop performance during periods of climate uncertainty. However, model performance depends on the quality and continuity of weather data, regional calibration, and the extent to which ET_o estimates are linked to crop-specific growth stage and soil moisture conditions. For this reason, AI-based irrigation management should be interpreted not simply as a predictive exercise, but as a climate-adaptive crop management strategy in which algorithm selection, environmental input variables, and local validation together determine practical effectiveness in the field.

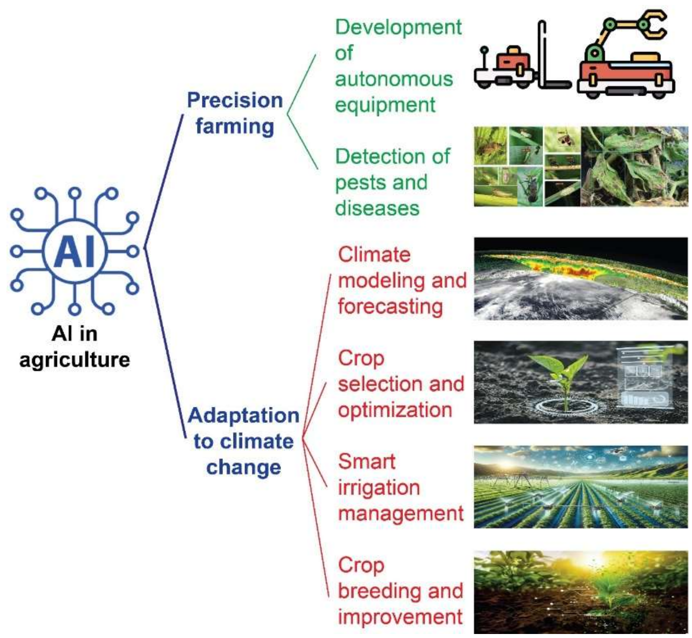

Figure 1. Applications of artificial intelligence in agricultural cultivation.

The application of AI in climate modeling and forecasting is becoming increasingly important in the context of global climate change. AI, with its ability to process and analyze vast amounts of data, has enabled advanced climate models to predict climate conditions more accurately than traditional methods. Using of machine learning and deep learning algorithms, AI can analyze data from sources such as historical weather data, satellite data, and climate variables to build short-term and long-term forecasting models. These models help farmers and managers better understand climate trends, enabling them to make informed decisions that minimize risks and optimize production. One of the specific applications of AI in climate modeling and forecasting is predicting extreme weather events such as droughts, floods, and prolonged heat waves. Thanks to the ability to analyze real-time data from environmental sensors and satellite images, AI systems can provide early warning of these phenomena, allowing agricultural communities to prepare in advance and minimize damage. For example, if AI predicts a drought, farmers can adjust their irrigation plans and choose drought-resistant crop varieties to maintain productivity. In this way, AI not only helps protect crops but also contributes to ensuring food security amid increasingly complex climate change. In addition, AI can also integrate with smart agricultural management systems to make farming recommendations based on climate models. For example, AI can recommend optimal planting and harvesting schedules, based on weather forecasts and climate conditions for each crop season [26]. This helps farmers not only avoid climate risks but also make the most of favorable conditions to improve productivity and quality of agricultural products. Overall, the application of AI in climate modeling and forecasting not only makes agriculture more sustainable but also contributes to building a safe and resilient food system to address future climate challenges.

The application of AI in crop selection and optimization is advancing rapidly in modern agriculture, particularly amid climate change and rising food demand. AI uses machine learning algorithms to analyze large amounts of data from sources such as climate, soil, and crop genetics, thereby making recommendations on the best suited crop varieties for each farming area's specific environmental conditions. This not only helps farmers choose crop varieties with high yields and strong pest and disease resistance, but also optimizes the use of resources such as water, fertilizer, and land, thereby increasing farming efficiency and protecting the environment. One of the prominent applications of AI in crop optimization is the ability to predict the performance of crop varieties under different climatic conditions. By analyzing historical data on weather, seasons, and crop yields, AI can predict which crop varieties will perform best under forecast weather conditions for a given season [13], [14]. This helps farmers minimize risks from climate change and maximize yields, ensuring that resources are used most efficiently. Furthermore, AI also aids in developing new crop varieties through the breeding process. By analyzing genetic data and identifying beneficial genetic traits, AI helps agricultural researchers develop crop varieties that are more resistant to adverse factors such as drought, high temperatures, and diseases. This not only meets the food needs of a developing world but also contributes to building a more sustainable agriculture. AI not only improves crop performance and quality but also opens new opportunities for future development of the agricultural industry.

The application of AI in smart irrigation management is driving significant improvements in the agricultural industry, helping optimize water use and increase farming efficiency. AI, with its ability to analyze data from various sources such as soil sensors, weather data, and satellite imagery, can accurately and timely predict crop water need. In this way, AI-driven smart irrigation systems can deliver the right amount of water at the right time and in the right place, avoiding water wastage and ensuring that crops are always supplied with enough water to thrive. One of the biggest benefits of AI in smart irrigation management is its ability to respond quickly to changes in environmental conditions. For example, when the weather forecast indicates imminent rain, the irrigation system can automatically reduce or stop irrigation to avoid excess water, thereby saving resources and minimizing the risk of crop flooding [27], [28]. Conversely, in drought conditions, AI can optimize irrigation schedules using real-time data from soil moisture sensors and crop water needs, ensuring water is used most efficiently while maintaining crop yields. Furthermore, AI in smart irrigation management also helps farmers minimize negative environmental impacts, such as reducing nutrient and chemical leaching into groundwater. By optimizing water use, AI not only reduces production costs but also contributes to the protection of water resources and the sustainability of ecosystems. In the context of climate change and increasingly scarce water resources, the application of AI in smart irrigation management is an important solution to help agriculture become more efficient, more sustainable, and better prepared to face future challenges.

The application of AI in breeding resilient crops is driving important advances in the agricultural industry, especially amid climate change and growing environmental challenges. AI enables researchers to analyze large volumes of genetic and environmental data to identify genetic traits associated with tolerance to adverse factors such as drought, high temperatures, pests, and poor soil. By using machine learning and deep learning algorithms, AI can predict which crop varieties will grow best in harsh conditions, thereby supporting the selection and breeding of new crop varieties with high adaptability. One of the prominent applications of AI in breeding resilient crops is the ability to shorten the time to research and develop new varieties. Instead of years of field testing, AI can simulate environmental conditions and predict the performance of different crop varieties, helping researchers quickly identify breeding potential candidates. This not only speeds up the development of new crop varieties but also reduces the costs and resources required for research. Crop varieties developed with the help of AI can be drought-tolerant, pest-resistant, or grow well in saline soil, meeting food needs in harsh environmental conditions. Furthermore, AI plays an important role in maintaining and enhancing the genetic diversity of crop varieties, a key factor in ensuring crop resilience to sudden environmental changes. By analyzing data from many different sources, AI can detect and preserve rare genes that are valuable for breeding resilient crops. This helps maintain genetic diversity and provides a foundation for developing future-proof crop varieties. By applying AI to breeding resilient crops, the agricultural industry can be better prepared for future challenges, from climate change to population growth and food demand. AI not only improves the efficiency and speed of breeding but also contributes to sustainable agricultural development, creating resilient crops that meet global food needs and protect the environment.

The application of AI in weather-responsive agriculture is bringing significant changes to the agricultural industry, helping farmers optimize production and minimize risks from climate change. AI, with its ability to analyze real-time data from sources such as weather forecasts, environmental sensors, and satellite imagery, can help farmers adjust farming activities in response to rapidly changing weather conditions. Instead of relying on traditional methods or intuition, farmers can use AI to make precise decisions about planting, irrigation, fertilization, and harvesting times, ensuring that crops receive the best care for each specific weather condition. One prominent application of AI in weather-responsive agriculture is to predict and manage extreme weather events such as storms, droughts, or cold spells. By analyzing large amounts of data from various sources, AI can accurately predict these phenomena, helping farmers prepare in advance and adjust farming activities accordingly. For example, if AI predicts an impending drought, smart irrigation systems can automatically increase irregation of crops before the drought begins, ensuring crops have enough water to grow and minimizing damage. Conversely, if heavy rain is forecast, AI can adjust fertilizer application to avoid leaching and nutrient waste, while protecting the environment from pollution. AI also assists in optimizing farming schedules based on weather data. By analyzing historical data and current weather conditions, AI can recommend optimal planting and harvesting times to maximize crop yield. This not only helps farmers avoid risks from bad weather but also makes the most of favorable weather conditions, thereby improving production efficiency and profits. By applying AI to weather-responsive agriculture, farmers can better manage the unpredictable elements of the climate while protecting crop yield and quality. AI makes agriculture more resilient and sustainable, meeting the challenges of climate change and ensuring a stable food supply in the future.

3. Some notes on applying artificial intelligence to farming in Vietnam

In the context of the 4.0 industrial revolution advancing rapidly, the application of AI in agricultural cultivation has opened up significant opportunities for the Vietnamese agricultural sector. AI promises to bring about remarkable improvements in productivity, optimize resource use and minimize negative environmental impacts. However, to fully harness AI's potential within Vietnam's agricultural sector, careful consideration must be given to key enabling factors, including digital infrastructure, education and capacity building, cost-effectiveness and accessibility, integration with traditional agricultural practices, data security, and adaptability to local conditions.

Digital infrastructure plays an important role in the implementation and effectiveness of AI applications in agricultural cultivation. For AI to operate optimally, there needs to be strong investment in the core components of digital infrastructure, including sensor systems to collect data from the agricultural environment, powerful servers to process large amounts of data, and especially a stable internet network to transmit data in real time. However, the reality is that in many rural areas of Vietnam, internet infrastructure is still weak, transmission speeds are slow and coverage is limited. This can be a major obstacle in applying AI to agricultural production, where the accuracy and timeliness of data are key factors. Therefore, upgrading and expanding the internet network and developing digital infrastructure in rural areas are essential, not only to support AI applications but also to promote the comprehensive development of smart agriculture in Vietnam.

Training and awareness raising are key to ensuring the success of AI adoption in agriculture in Vietnam. Farmers and agricultural managers need to be equipped with the necessary knowledge and skills to effectively use AI technologies in practice. This requires not only an understanding of how to operate and maintain AI systems, but also raising awareness of the benefits that AI can bring to the production process, such as optimizing resource use, increasing productivity and minimizing risks. Training needs to be tailored to the level and practical needs of farmers, ensuring that they not only master the theory but also apply it in their daily farming activities. At the same time, creating AI awareness programs will help address concerns and psychological barriers to new technology, promote the acceptance and widespread application of AI in the agricultural community, thereby contributing to the sustainable development of Vietnam's agricultural sector.

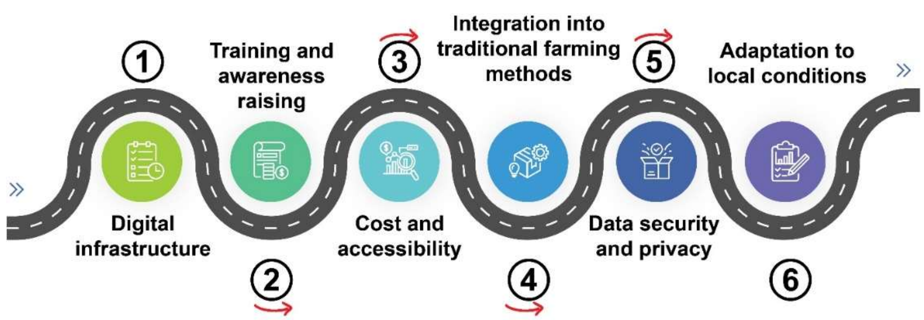

Figure 2. Some notes when applying artificial intelligence in agricultural production in Vietnam.

Cost and accessibility are two major challenges when implementing AI technology in agriculture, especially for small-scale farmers. While AI has the potential to bring many benefits, such as increased productivity, resource optimization, and risk reduction, the initial cost of adopting this technology can be very high. This includes equipment purchase, system installation, training, and maintenance, which can be a barrier for many farmers with limited resources. To address this issue, governments or NGOs should provide financial support policies such as preferential loans, subsidies, or incentive programs. In addition, public-private partnership (PPP) models can also play an important role in sharing costs and risks and promoting AI adoption in agriculture. These models could include collaboration among governments, private businesses, and community organizations to provide AI technology and services at more affordable prices, thereby enabling farmers to access and adopt AI more easily and effectively.

Integrating AI with traditional farming methods is an important strategy to ensure that new technology does not devalue the experience and knowledge accumulated over generations. AI offers powerful tools for analyzing data and optimizing production processes, but farmers' deep understanding of soil, crops, and local climate is indispensable. Rather than eliminating traditional methods, AI should be used as a complementary tool, supporting farmers to make more accurate and efficient decisions based on real data. Combining AI with farmers' practical experience can create a sustainable farming model where technology and tradition coexist and complement each other. For example, AI can predict the optimal irrigation time based on weather data. However, the final decision should still be based on the farmer's understanding of soil characteristics and specific crop needs. In this way, AI not only helps improve production efficiency but also respects and preserves traditional values, ensuring that the transition to high-tech agriculture takes place in a harmonious and sustainable manner.

Data security and privacy are important factors that require special attention when implementing AI technologies in agriculture. As AI increasingly relies on data to provide smart solutions and optimize farming processes, data collection, storage, and processing are becoming more common. However, this also poses significant security and privacy challenges. Farmers need to be assured that their personal information and farming data are strictly protected, used only for agreed purposes, and not misused or disclosed to unauthorized third parties. To ensure security, AI solutions need to incorporate robust data protection measures, including encryption, access controls, and advanced cybersecurity monitoring systems. Furthermore, compliance with data protection regulations such as the European General Data Protection Regulation should also be considered and applied, even at the national or regional level. In addition, farmers need to be clearly informed about how their data will be used, who will have access, and have mechanisms to control and monitor its use. Focusing on data security and privacy not only helps build farmers' trust in AI technology but also creates a healthy and transparent environment for the development of digital agriculture. This ensures that the benefits of technology do not come with unwanted risks, protects farmers' rights, and contributes to the sustainable development of the agricultural sector.

Adapting to local conditions is an important factor to consider when implementing AI solutions in agriculture in Vietnam. With diverse climates and terrains, from the Red River Delta to the Northwest highlands and the Mekong Delta, each agricultural region in Vietnam has its own requirements and challenges. Therefore, AI solutions need to be customized for each region, ensuring they can effectively meet the specific needs of local farmers. Developing AI models based on local data is necessary to achieve high accuracy and optimize farming processes. For example, data on soil, climate, crops, and farming practices for each region should be integrated into AI models to produce accurate forecasts and recommendations. An AI system that can work effectively in the Mekong Delta, with its tropical monsoon climate and complex irrigation system, will need to be adapted to the dry conditions and mountainous terrain of the Central Highlands. In addition, the involvement of local experts and collaboration with local agricultural research institutions are also important in developing and deploying customized AI solutions. This not only ensures the accuracy and effectiveness of the solutions but also helps increase acceptance among farmers, as they see that the technology is designed to meet their exact challenges and needs. Adapting AI to local conditions will greatly contribute to the success of smart agriculture programs in Vietnam, promoting sustainable and efficient development of the agricultural sector amid climate change and international integration.

4. Conclusion

This study shows that AI is becoming a powerful tool for revolutionizing the agricultural biotechnology industry, especially in the context of global challenges such as climate change and rising food demand. AI not only optimizes farming processes through big data-based analysis and prediction, but also contributes significantly to the development of new crop varieties with greater resilience, more efficient resource use, and environmental sustainability. In the field of precision farming, AI has proven to be highly effective in optimizing the use of resources such as water, fertilizers, and pesticides, while providing accurate predictions of planting and harvesting times, helping farmers increase productivity and minimize risks. Applications such as object detection, disease and pest detection have opened new possibilities for crop monitoring and management, helping farmers make accurate timely decisions and thereby increasing the quality and efficiency of agricultural production. AI also plays an important role in adapting agriculture to climate change, from developing resilient crop varieties to smart irrigation management and adjusting farming practices based on weather conditions. The ability to predict extreme climate events and optimize farming processes to cope with these challenges has made agriculture more resilient and sustainable. However, for AI to fully realize its potential in Vietnamese agriculture, fundamental factors such as digital infrastructure, training and awareness raising, cost and accessibility, integration with traditional methods, data security and privacy, and adaptability to local conditions need to be taken into account. These factors not only help deploy AI effectively but also ensure that this technology will deliver sustainable long-term benefits to Vietnam's agricultural sector, while contributing to the comprehensive development of smart agriculture in the digital era.

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