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AI-Based Diagnostic Tools for Abiotic Stress Management in Smart Agriculture

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Abstract: Abiotic stress, such as drought, salinity, heat, cold, and imbalance of nutrients are leading cause of low crop productivity and a significant threat to the world's food security, especially in the changing climatic conditions. With the support of artificial intelligence (AI), smart agriculture proposes creative ways of early detection and successful management of such stresses. In this paper, an overview of AI-based diagnostics tools applied in the management of abiotic stress in contemporary agricultural systems is provided. Different types of machine learning and deep learning algorithms, such as neural networks, support vector machines, and computer vision models, are mentioned in terms of their capacity to process data collected through remote sensing platforms, Internet of Things (IoT) sensors, and field-based imaging systems. Through these tools, real-time monitoring, accurate determination of stress, and predictive decision-making on precision farming are possible. Another aspect that is noted in the paper is the participation of data integration, automation, and predictive analytics in enhancing the efficiency of resource-use and resilience of crops. The problems of data availability, model interpretability, infrastructure constraints, and scalability are reviewed, as well as the possible direction of future research. On balance, the paper focuses on the point that AI-based diagnostic mechanisms have a tremendous potential to improve sustainable farming procedures, lower negative environmental effects, and promote climate-resilient food production machinery.

Keywords

Artificial Intelligence; Abiotic Stress; Smart Agriculture; Precision Farming; Machine Learning; Deep Learning; Crop Stress Diagnosis; IoT; Remote Sensing

1. Introduction

Abiotic stressors, including drought, salinity, and excessive temperatures, play a key role in reducing the world's agricultural productivity because they cause undesirable morphological, physiological, biochemical, and molecular changes in crops. These environmental issues require sophisticated monitoring systems to reduce their effect since conventional systems are labor-intensive, devastating, and lacking in the ability to intervene on time and in large areas of agricultural fields (Muhammad et al., 2025). Non-destructive and scalable, real-time stress monitoring and early detection solutions are provided by the emergence of smart agriculture, which involves the combination of artificial intelligence and high-throughput phenotyping technologies. The purpose of the paper is to examine the state-of-the-art in AI-based methods of abiotic stress detection in crops, assess their potential and limitations more critically, and explore their future opportunities in improving crop resilience and yield security. In particular, it will revise the field of machine learning and deep learning tools, and specifically, the computer vision methods that will ensure accurate and fast evaluation of crop reactions to a wide range of environmental misfortunes (Orka et al., 2023). Moreover, it will address how these AI solutions, together with multi-omics data and sophisticated phenotyping, can expedite the creation of climate-resilient crops essential to sustainable agricultural activities (Thingujam et al., 2025). The review will offer valuable lessons to scientists, agronomists, and policymakers in their attempt to increase crop yields using improved methods of stress sensing and control, which will ultimately result in world food security. The growing world population, which is expected to reach more than 10 billion in 2050, requires the enhancement of agricultural productivity, and this requires the creation of stress-resistant types of crops, which requires exact and robust technological change (Gou et al., 2024).

Climate change, however, increases abiotic stresses such as drought, salinity, and extreme temperatures, which are major threats to agricultural sustainability and food security. The environmental problems are extreme to the physiology of crops, causing significant losses of yields and making it difficult to develop resilient varieties (Angidi et al., 2025). New approaches are therefore necessary in order to precisely measure and describe the plant responses to these stressors, beyond the traditional, typically destructive, and laborious phenotyping approaches (Nguyen et al., 2025). The artificial intelligence augmented high-throughput phenotyping platforms offer an efficient and non-invasive way of measuring complex plant phenotypes and their responses to changes in the environment, thus circumventing the shortcomings of the conventional methods (Choudhury et al., 2024).

These abilities are essential in proactive interventions, resource management, and development of crops with greater resistance to unfavourable environmental conditions (Angidi et al., 2025). Combining these advanced phenotyping methods with multi-omics information, including genomics, transcriptomics, proteomics, and metabolomics, will also allow the development of a comprehensive perspective on plant response to stress, which will open the possibility of the discovery of new genetic and pathway markers of stress-tolerance (Thingujam et al., 2025). This combined methodology, which makes use of artificial intelligence to interpret data, is essential in helping to bridge the gap between genotype and phenotype and speeding up crop breeding programs to create climate-smart agricultural programs. This paper aims to provide a review of the current situation in the use of artificial intelligence to integrate into high-throughput phenotyping to identify abiotic stress in crops, with references to the ways in which such technologies can overcome the limitations of traditional stress sensors (Abdulraheem et al. 2026; Abdulraheem, et al. 2025).

2. Types of Abiotic Stresses in Agriculture

The abiotic stresses involve various categories of conditions in the environment, and as a whole, these conditions greatly hinder the productivity of agriculture all over the world. These stressors are out of the optimum growing conditions and are causing significant losses in crop yields, which endangers the world's food security. These dangers have been magnified by the gradual increase in climate change scenarios, which have prompted alterations in morphological, biochemical, and physiological processes of plants. Such changes can typically be in the form of decreased growth, photosynthesis, and reproductive processes, which leads to low crop quality and quantity. It is important to understand the exact mechanisms through which these various abiotic stresses influence plant biology to come up with resilient agricultural systems. This general discussion will be in-depth to explore the complex effects of drought, salinity, temperature extremes, nutrient deficiencies, heavy metals, and pollutants on crops.

2.1Drought Stress

Drought as a form of abiotic stress is a common and widespread challenge that has a detrimental effect on plant physiological functions, causing low crop yields and quality (Muhammad et al., 2023). Drought affects not only the cellular and molecular mechanisms but also causes oxidative stress, changes in gene expression, and disruption of metabolic pathways, which are required in growth and development

(Moulick et al., 2024; Santos et al., 2022). Lack of water forces plants to undergo some complex adaptive mechanisms, including stomatal closing in a bid to preserve moisture, which inevitably reduces photosynthetic and carbon assimilation (Kochar et al., 2020; Fudzagbo and Abdulraheem). This decrease in photosynthetic efficiency, along with other disruptions caused by drought, has a detrimental effect on the growth and development of plants, which eventually causes massive biomass and productivity wastes (Zhang et al., 2024; Swain et al., 2023). Moreover, during drought periods, the soil water potential is commonly reduced, preventing the uptake and acquisition of the necessary nutrients, which, again, reduces the stress of plants and decreases their overall vigor (Yadav et al., 2020). The rise in both frequency and severity of droughts is a major threat to the sustainability of agricultural production, with the effect of climate change being a major cause of the increase in droughts, which is expected to cause up to 70% reductions in essential staple food crops (Arjumend et al., 2022).

2.2 Salinity Stress

Another major problem that can affect agricultural productivity is salinity, which is an excessive concentration of salts in the soil and impairs water absorption and leads to toxicity of the ions (Yadav et al., 2020). This osmotic pressure, which is combined with the effects of the particular ions, prevents homeostasis and metabolic processes in the cells, resulting in decreased plant growth and development (Saharan et al., 2022; Santos et al., 2022). Salt (especially sodium chloride) in high concentration disrupts the absorption and transport of nutrients, resulting in nutrient imbalances and oxidative damage (Yadav et al., 2020). As an example, the high concentration of sodium chloride is able to cause oxidative stress in legumes, which adversely impacts the nutrient quality of seeds, nodulation, and overall plant development (Zulfiqar et al., 2024; Abdulraheem & Charles, 2013). Increasing global temperatures and changing precipitation patterns also aggravate the problem of salinity, particularly in dry and semi-arid zones, by increasing the speed of evaporation and concentrating salts within the root zone (Santos et al., 2022). Salinity affects an area of about 6% of the cultivated land in the world and poses a serious constraint on agricultural production (Isıyel et al., 2024). Salinity has a negative impact, which is aggravated by the interaction with other stress factors affecting the ecosystem, e.g., drought, making sustainable crop production more difficult (Waseem et al., 2023; Zhang et al., 2025).

2.3 Temperature

Extremes: Excessively high and low temperatures are both harmful to the growth, development, and yield of crops because they interfere with the normal physiological processes of crop growth, development, and enzyme activity. Extreme thermal conditions may also change the fluidity of the membrane and protein structure, affecting the activity of the enzymes and, in general, the physiological reactions of the plants (Sena et al., 2024). Temperature variations and forecasting models play a significant role in the prediction and reduction of the negative impact of these stressors, though the effectiveness of passive techniques such as irrigation has been compromised over the years (Sisodia and Sharma, 2023). When ambient temperatures exceed the optimal range of a plant, heat stress takes place, which mainly affects the fluidity of the membrane and destabilizes the photosystem, causing disrupted photosynthesis (Muhammad et al., 2025).

2.4 Heavy Metals and Pollutants

The availability of heavy metals and other environmental pollutants in farmlands and water bodies is a major form of abiotic stress, which directly affects the growth and productivity of plants and has serious health hazards to consumers. These poisonous elements, among others, lead, cadmium, arsenic, and

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mercury, accumulate in the plant bodies, disrupting vital biochemical pathways, causing oxidative stress, and thus decreasing agricultural output (Singh et al., 2023). In addition to direct phytotoxicity, some heavy metals have also been reported to have a profound impact on the photosynthetic process and, consequently, the decrease in crop production was significant (Alhaithloul et al., 2020). Contamination of soils with different heavy metals is an issue of high importance to the environment because of their negative effect on agricultural soils, resulting in detrimental effects on many plant physiological functions that ultimately reduce crop productivity (Michael, 2021). These wastes may also modify the microbial communities in the soils, further reducing the nutrient cycling and plant health, and making the problem of sustainable agriculture even more difficult. This widespread issue is being caused by increased trapping of heavy metals into the atmosphere due to human actions, making the interaction between industrialization and the possibility of agricultural sustainability complex (Yadav et al., 2020).

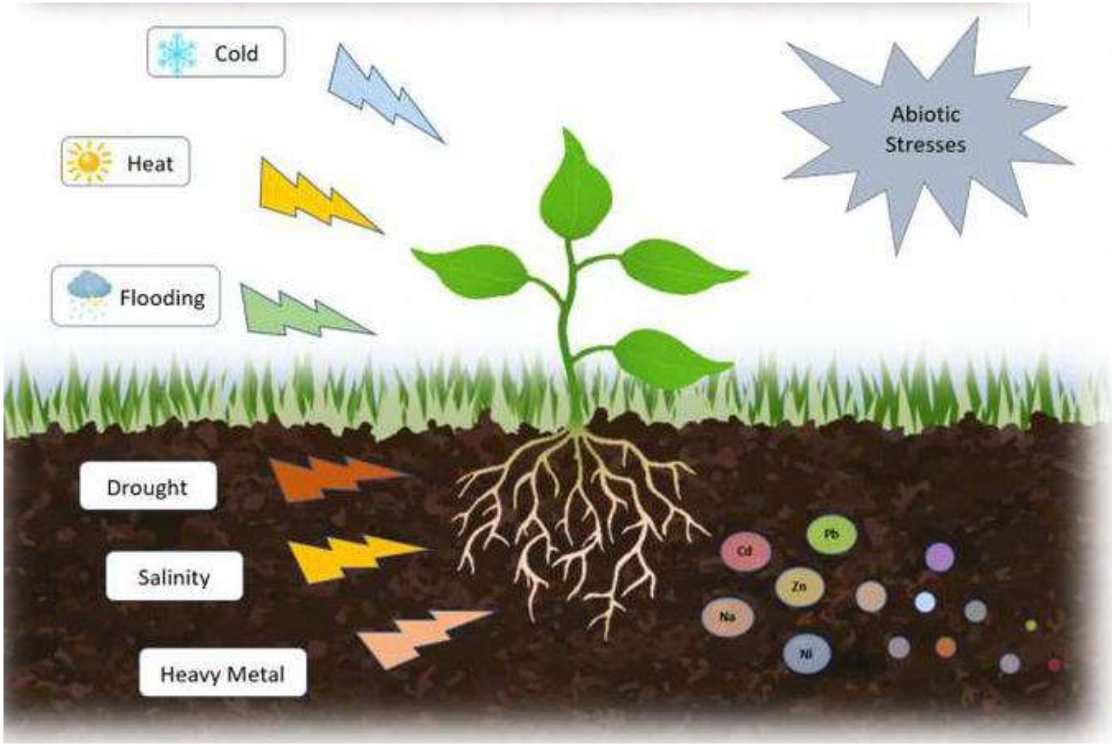

Figure 1. Different types of abiotic stresses (Kul et al., 2021)

3. Overview of AI in Agriculture

Artificial intelligence being integrated into all these various technological fronts constitutes the paradigm shift towards smart agriculture that would provide solutions to the major problems facing the world today, including food insecurity, climate change, and resource deficit (Keskes, 2025). This multidimensional strategy, which is commonly referred to as digital agriculture, is based on the use of sophisticated computational frameworks that are used to maximize all or most agricultural production processes, such as planting (precision) and harvesting (yield prediction and pest control) (Fuentes-Peñailillo et al., 2024). Such AI applications are the most crucial, as it includes crop, water, and soil management, as well as sophisticated methods in fertigation and accurate prediction of crop yields, which will increase efficiency and sustainability in agricultural processes (Saha et al., 2024). This integration of technologies highlights a turning point in the direction of the intelligent agricultural system, and the use of data-driven information would provide farmers with the opportunity to make knowledgeable choices, supporting the sustainability and simplified productivity of agriculture (Saha et al., 2024).

3.1Machine Learning (ML)

Models of machine learning process large agricultural data, such as soil composition and weather patterns, to predict the most suitable time to plant, predict crop yields, and detect possible outbreaks (Kumari and Nafchi, 2024). Support Vector Machines, as well as Random Forests, are also useful in supervised learning applications that can classify crops by growth patterns, forecast an ideal harvest time, and detect pest and disease susceptibility (Rane and Choudhary, 2023). On the other hand, unsupervised learning is very effective at finding latent patterns in very complex agricultural data, like novel disease vectors or previously unseen participation of environmental factors in crop health (Otieno, 2023). Moreover, reinforcement learning approaches are being actively utilized to optimize irrigation and nutrient delivery systems by adjusting to the current environmental conditions to make the best use of resources (Babakhouya et al., 2023). Such predictive and adaptive features make it possible to achieve considerable deliveries in resource availability and operational effectiveness in the agricultural systems (Kumari et al., 2025).

3.2 Deep Learning (DL)

Deep learning, a specific subdivision of machine learning, is a neural network with multiple layers that can be used to handle complex agricultural data and can be particularly useful in such tasks as image recognition to detect diseases and complex predictive modeling to predict yields (Ali et al., 2025; Saha et al., 2024). The AI is exceptionally effective at working with unstructured data, including drone or sensor images, and that way, this AI can accurately detect the stress of plants, nutrient deficiencies, and pest infestations at an early stage (Akintuyi, 2024). An example is the Convolutional Neural Networks, which have transformed the analysis of aerial data to enable pixel-by-pixel evaluation of crop health conditions and interventions targeted (Ugwu et al., 2025). Recurrent Neural Networks, in their turn, are utilized in analyzing the time-series data, i. e., historical weather patterns and growth cycles, to predict future yield with impressive accuracy (Rane et al., 2024). They can be extended to identifying anomalies in large data sets and, in this way, actively interfere in irrigation, fertilizing, and pest control, and reduce losses by minimizing waste resources (S.N. et al., 2024). In addition to these uses, deep learning also enables more sophisticated phenotyping of genetic expressions and environmental interactions, resulting in more resilient and productive crop varieties (Zidan & Febriyanti, 2024).

3.3 Computer Vision

Based on the achievements of deep learning in analyzing images, computer vision systems provide a non-invasive and highly accurate method of crop health monitoring, weed detection, and fruit ripeness, thus automating much of the labor-intensive parts of agriculture (Rane et al., 2024). These systems combine high-resolution cameras and advanced algorithms to conduct real-time analysis of the morphology and the changes in color in plants and enable the early identification of the stress indicators that usually cannot be observed by the naked eye. As an example, specific types of imaging, such as hyperspectral and multispectral imaging, applied in combination with the use of sophisticated computer vision models, can be used to detect individual deficiencies or the presence of pathogens before they are felt, and a specific area may be treated (Sherkhane & Ratnaparkhi, 2024). Such accuracy of identification and intervention can reduce the unselective use of pesticides and fertilizers, which is why the agricultural process will become more sustainable and prevent the degradation of the environment (Rane et al., 2024).

3.4 Remote Sensing and Drones

IoT devices, which consist of a broad range of sensors both in fields as well as in machinery, mean constant real-time data on key environmental factors and physiological parameters, including soil moisture, temperature, humidity, and nutrient levels, which can be used to manage farm functioning on a hyper-localized and adaptive basis. This type of granular data collection is the foundation of precision agriculture, as granular data enables farmers to optimize irrigation, nutrient delivery, and pest control interventions with greater accuracy than ever before. Furthermore, the combination of IoT sensor networks with AI algorithms also enables the prediction of analytics and the conversion of raw data into actionable insights, facilitating proactive decision-making (Rane and Choudhary, 2023; Sharma and Shivandu, 2024). Such an extensive data infrastructure also contributes to automating numerous agricultural operations, which increases the efficiency of operations and the number of manual workers (Zhang et al., 2025). Such interdependent instruments enable real-time observation and data gathering on several farm-related parameters making farmers to make effective decisions and resource allocation optimization (Rane & Choudhary, 2023).

4. AI-Based Diagnostic Tools for Abiotic Stress

The adoption of artificial intelligence has transformed food production, especially in the early detection and control of abiotic stresses, which are highly affecting crop production and food security (Gou et al., 2024; Muhammad et al., 2025). They are non-invasive and pragmatic substitutes of the traditional approach, which relies on the latter tools to examine the health of crops using advanced computer visualization and machine learning (Orka et al., 2023). As an example, a more advanced imaging modality combined with the AI algorithm can be used to detect the signs of stress much faster and more precisely than a human eye could do (Angidi et al., 2025). In this strategy, multi-omics data such as genomics, transcriptomics, proteomics, and metabolomics are used to reveal genetic pathways that give stress resilience (Thingujam et al., 2025). Additionally, the ability of AI to handle high-throughput data, accessible at different locations, including remote sensing stations and in-field sensing devices, will provide an opportunity to monitor all environmental factors and plant physiological reactions and provide the information on complex stress interactions (Gou et al., 2024). Such a holistic methodology is essential to devise the resistant to stress crop varieties and apply precision farming techniques to reduce losses (Gou et al., 2024). Moreover, the harmony between imaging sensors and AI has played a significant role in the identification of stress symptoms in plants, but the analysis of data is also one of the primary issues because of the difficulties with standardized data collection, analytical procedures, and the choice of the most suitable imaging sensors and AI algorithms (Walsh et al., 2024).

Dialectic stresses, including drought, salt, and heat stresses, which are compounded by climate change, made using highly effective diagnostic instruments the only way to accurately determine crop physiology and yield losses (Angidi et al., 2025). To overcome these obstacles, it is necessary to eliminate the technological obstacles of scalability of the cost and the adaptability of the fields and integration of AI to provide real-time data analysis and improve the high-throughput phenotyping use in breeding programs (Angidi et al., 2025). Further breeding phenotyping, with tools such as drones and hyperspectral images, can also radically speed up the breeding programs by enabling high-throughput trait tracking (Thingujam et al., 2025). Such cutting-edge resources are essential to determine stress-resistant genotypes through the combination of multi-omics data with phenomics-focused pipelines, which makes it possible to learn more about how plants respond to different abiotic conditions (Muhammad et al., 2025). It is a synergetic integration of AI and multi-omics that will enable the bridging of the gap between genotype and phenotype with an improved accuracy of high-throughput crop phenotyping, genotyping, and envirotyping (Angidi et al., 2025; Khan et al., 2022). Such integration allows transforming complicated biological data into measurable values, which are required to be analyzed by computers and create predictive models (Murmu et al., 2024). This will help to develop AI-based diagnostic equipment that will be able to interpret minor physiological signals, which may warn of the occurrence of abiotic stress early, and it will direct appropriate intervention plans (Maheswari et al., 2024).

Dynamically imaged methods, especially in vivo biosensors, allow real-time high-spatial-resolution assessment of hormone levels, glutathione redox states, and transients of reactive oxygen species, and deliver the essential information about the plant physiological response to abiotic stress (DIETZ, 2021). This comprehensive surveillance, together with AI analytics, will be able to isolate individual stress processes and can hasten the creation of stress-sensitive types with the help of specific genome editing instruments (Raza et al., 2024). These optical techniques, which include different types of sensors and measurement of images, enable non-destructive and fast measurement of attributes of critical characteristics, such as root architecture, chlorophyll content, and canopy temperature in controlled and field settings (Angidi et al., 2025). This facilitates high-throughput phenotyping systems to acquire a huge volume of data through the entire life cycle of a plant to transcend the inefficiencies and errors of conventional phenotyping techniques (Farooqi et al., 2022). Such a high level of capability greatly speeds up the breeding process by revealing some desirable traits at the initial stage of plant development, which solves the problem of food security in the world (Munjal et al., 2023). When used on such high-dimensional data, machine learning algorithms can determine accurate associations between genotypes and phenotypes, which will speed the identification of genes that are associated with certain stress tolerance phenotypes like metal toxicity (Raza et al., 2024). These bioinformatics can be used to predict gene-environment interaction and can be used to identify new targets of genetic engineering to make crops more tolerant to diverse abiotic stressors such as drought, salinity, and heat using gene editing with the assistance of AI (Khan et al., 2025).

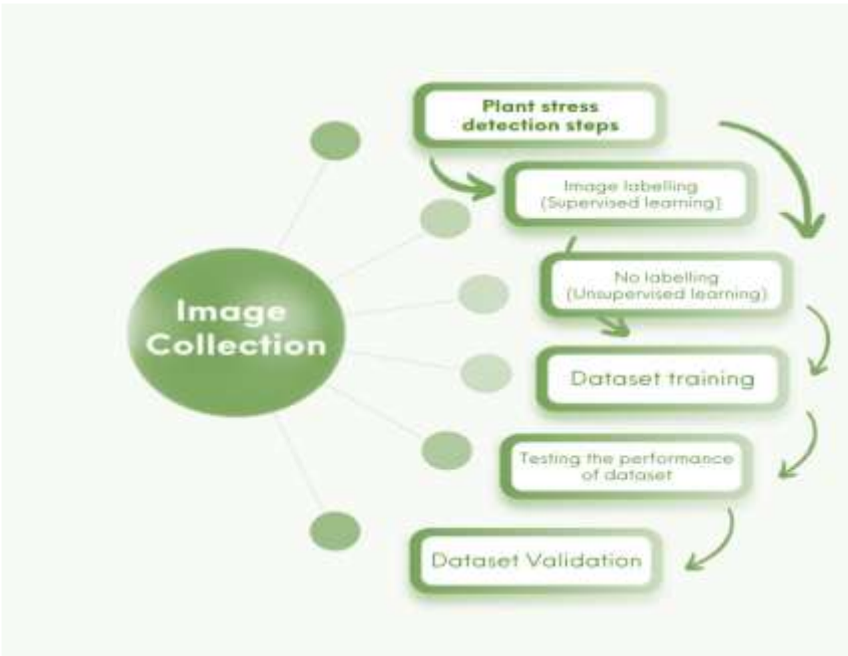

Figure 2. Artificial intelligence application in abiotic Stress management in plants

5. Future Prospects

The use of AI-based diagnostic tools in the smart agriculture of abiotic stress management will become groundbreaking. The next appearance of developments is supposed to be aimed at the incorporation of multi-source information, such as satellite images, sensor networks, weather forecasting, and genomic data, to be able to detect stress more accurately and in real time. Explainable AI (XAI) models will enhance the level of transparency and trust between farmers and agronomists by explaining the diagnostic decision-making process. Also, edge computers and low-power AI-based devices will enable quicker, field diagnosis of stress, with less reliance on cloud computing, and these technologies will be more available in remote and resource-constrained locations. The other significant future direction is the inclusion of predictive and prescriptive analytics. Instead of just detecting stress conditions, AI will predict stress occurrences and offer adaptive stress management techniques like optimization of irrigation programs, nutrient application and crop choice. AI researchers, plant scientists, and policymakers will also have to work together to develop standardized datasets, enhance model generalization across agro-climatic regions, and make the deployment ethically and sustainably. With falling costs and rising digital literacy, AI-based abiotic stress management tools will become popular and become part of climate-resilient and more sustainable agricultural systems.

6. Conclusion

The diagnostic tools developed using AI can provide an effective answer to the problem of the early identification and efficient management of abiotic stresses in smart agriculture. Using machine learning, deep learning, computer vision, and sensor technologies, these systems contribute to triggering data-driven decisions in time, improving crop productivity, resource-use efficiency, and environmental sustainability. Although there are difficulties in the area of data quality, infrastructure, and model interpretability, the continuous development and improvement in technology, along with the contribution of other disciplines, are quickly surmounting the limitations. To summarize, AI-based diagnostics is one of the most important elements of the future smart farming systems, and its potential to reduce the effects of climatic variability and guarantee global food security is significant.

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