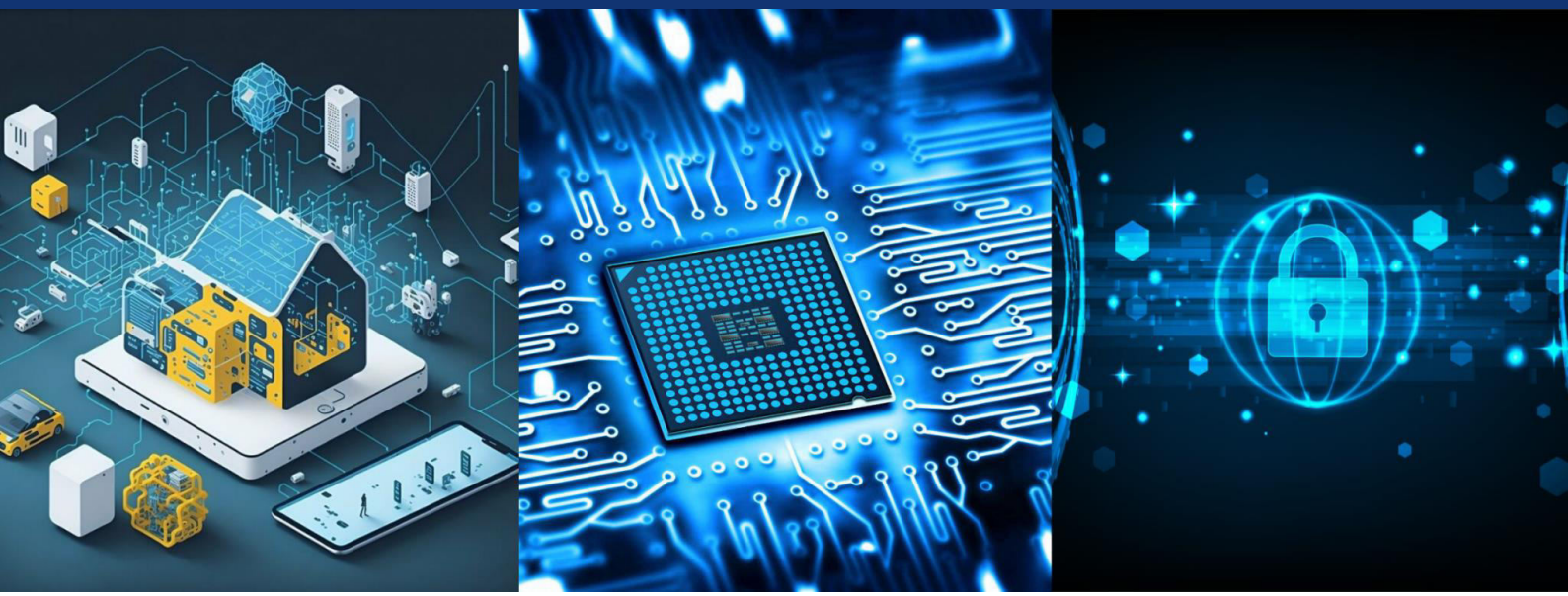
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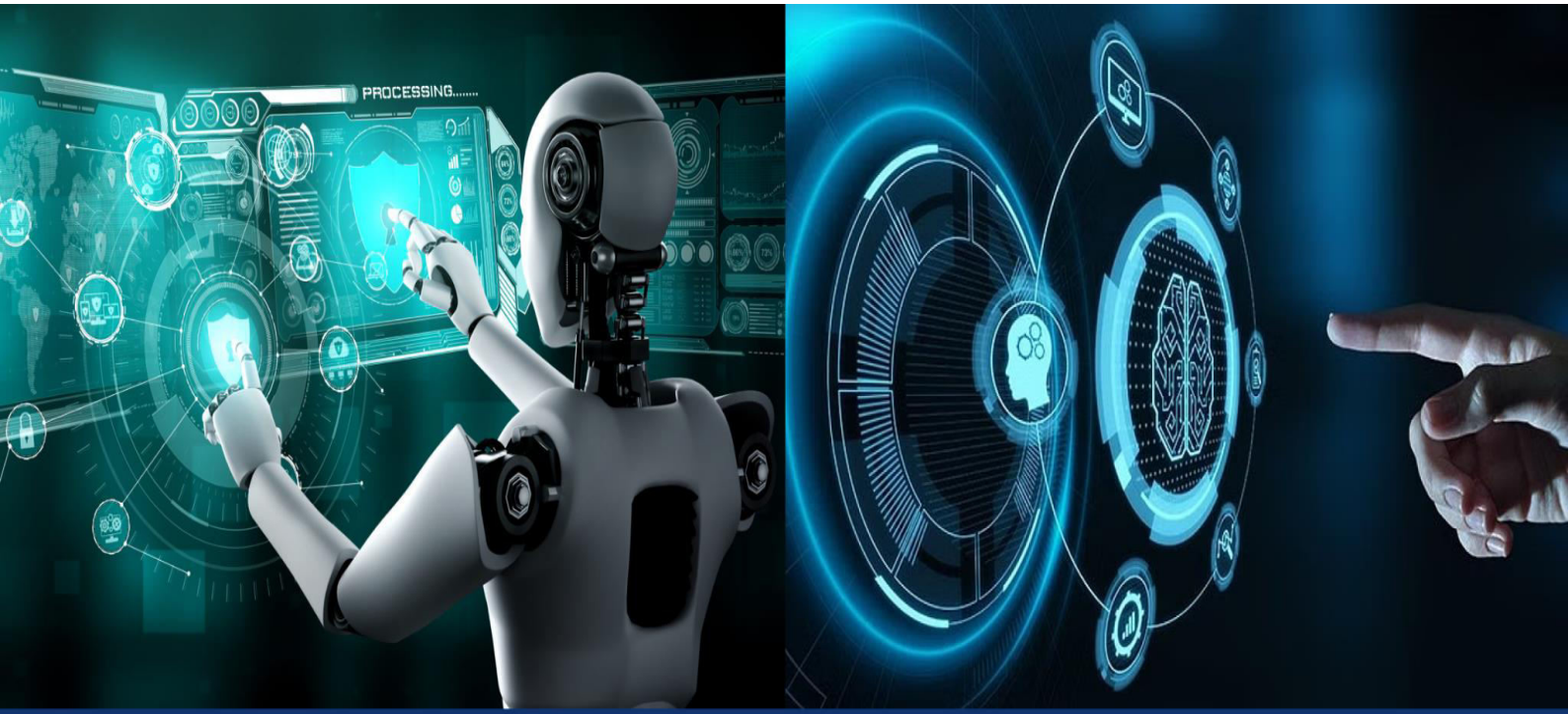
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Deep Learning Assisted Computer Vision Techniques for Smart Greenhouse Agriculture

G.Gowri, S.Dinesh Kumar, K.N.Sivakumar

Research Scholar, Department of Computer Science and Engineering, M.P.Nachimuthu M.Jaganathan Engineering College (An Autonomous Institution), Chennimalai, Erode, India

Department of Computer Science and Engineering, M.P.Nachimuthu M.Jaganathan Engineering College (An Autonomous Institution), Chennimalai, Erode, India

Associate Professor/ Head, Department of Computer Science and Engineering, M.P.Nachimuthu M.Jaganathan Engineering College (An Autonomous Institution), Chennimalai, Erode, India

ABSTRACT: With the escalating global challenges of food security and resource sustainability, innovative solutions like deep learning and computer vision are transforming agricultural practices by enabling data-driven decision-making. Provides a focused review of recent advancements in deep learning-enabled computer vision techniques tailored specifically for greenhouse environments. First, deep learning and computer vision fundamentals are briefly introduced. Over 100 studies from 2020 to date are then comprehensively reviewed in which these technologies were applied within greenhouses for growth monitoring, disease detection, yield estimation, and other tasks. The techniques, datasets, models, and overall performance results reported in the literature are analyzed. Tables and figures showcase real-world implementations and results synthesized from current research. Key challenges are also outlined related to aspects like model adaptability, lack of sufficient labeled greenhouse data, computational constraints, the need for multi-modal sensor fusion, and other areas needing further investigation. Future trends and prospects are discussed to provide guidance for researchers exploring computer vision in the niche greenhouse domain. By condensing prior work and elucidating the state-of-the-art, this timely review aims to promote continued progress in smart greenhouse agriculture. The focused analysis, specifically on greenhouse environments, fills a gap compared to previous agricultural surveys. Overall, research highlights the immense potential of computer vision and deep learning in driving the emergence of data-driven, smart greenhouse farming worldwide.

KEYWORDS: Green products, Computer vision, Farming, Agriculture, Crops, Deep learning, Air pollution, Agriculture, Convolutional neural networks

I. INTRODUCTION

The development of agricultural production can be broadly divided into four stages: the era of traditional agriculture, the era of mechanized agriculture, the era of automated agriculture, and the era of smart agriculture—characterized by unmanned operations and deep integration with computer science. Today, the digital revolution in agriculture is gaining momentum. During this structural transformation, the agricultural sector faces severe labor shortages due to a declining workforce and rural-to-urban migration, while societal demand for agricultural output continues to rise. This imbalance between labor scarcity and growing demand threatens agricultural productivity and sustainability. From a global perspective, as challenges related to food security and resource sustainability intensify, the need to reform agricultural practices and enhance productivity has become more urgent than ever. Pressing issues such as population growth, climate change, and urbanization—compounded by dwindling natural resources cast a shadow over the future. Agricultural progress plays a vital role in a nation's economy and survival.

As noted in, achieving sustainable agriculture requires improving production efficiency, adopting precision farming, and reducing waste on the demand side. Therefore, technological innovation and agricultural transformation are imperative. Traditionally, acquiring agricultural data was labor-intensive, time-consuming, and prone to errors. However, with the integration of computer science and agriculture, technologies such as remote sensing, digital

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applications, sensors, hyperspectral imaging, and artificial intelligence have ushered agriculture into an era of intelligent transformation.

Computer vision technology plays a pivotal role in this agricultural revolution. Thanks to its advancements, it has been widely adopted in smart agriculture. Deep learning, a field closely related to computer vision, enables automated feature extraction and learning from large-scale datasets, achieving unprecedented capabilities in image understanding. It demonstrates state-of-the-art performance in video analysis, facial recognition, image classification, biomedical applications, and health informatics. Moreover, its exceptional data processing and learning capabilities are proving indispensable in agriculture.

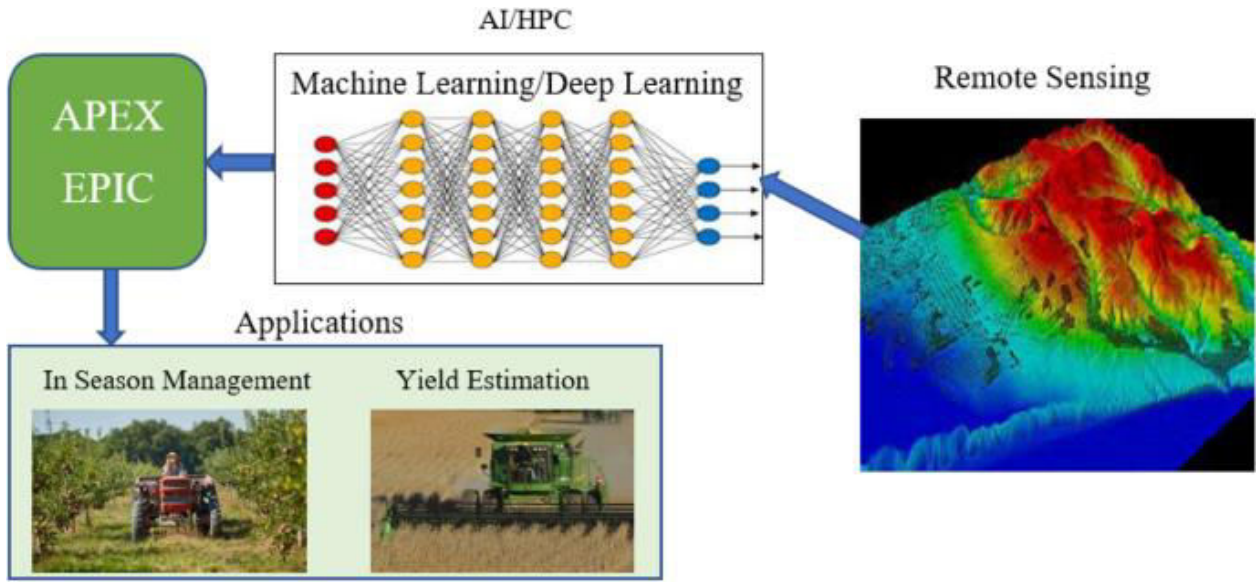


Fig 1: Deep Learning for Smart Agriculture and Precision Farming

Agricultural production is a complex and systematic industry involving a complete workflow from pre-planting preparation to post-harvest handling. This paper categorizes the agricultural production process into three key phases as follows. The first phase is preparation, which requires comprehensive land assessment, soil health evaluation, and crop suitability analysis. Modern soil testing has evolved into an intelligent system integrating spectroscopy, electrochemistry, molecular biology, and other technologies, significantly improving production efficiency and serving as a critical component in agriculture.

The second phase is crop growth management. This stage encompasses seed selection, growth monitoring, grading and classification, disease detection, and weed identification in fields. It directly determines crop yield, quality, and economic returns. The integration of computer vision and deep learning in this phase maximizes the potential of land, seeds, water, fertilizers, and other resources while mitigating risks. The final phase is harvesting and post-harvest handling. Crop growth environments are complex and seasonal, with harvest periods often concentrated within short timeframes. The methods of harvesting and processing directly affect product quality, shelf life, and market value. Against the backdrop of labor shortages and surging demand for crop yields, the transition toward automation and intelligent solutions has become an inevitable trend.

The rapid advancement of computer vision and deep learning has highlighted their pivotal role in agriculture. The Boolean search terms used in the Web of Science database were: (“agriculture”) AND (“computer vision”) AND (“deep learning”), with the time frame limited to articles from the past five years. The study initially screened nearly 3000 articles based on four thematic aspects. Subsequently, the top 10% most relevant articles were selected, and a manual screening was conducted based on their abstracts, resulting in a final selection of 100 articles.

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Prior to our work, several studies have reviewed research in this field. focused specifically on tea crops, summarizing applications of computer vision and machine learning across three key stages: cultivation, harvesting, and processing. introduced eight types of image segmentation methods and reviewed deep learning applications in agricultural image segmentation. analyzed deep learning models and discussed their use in plant disease and pest detection. The study by reviewed computer vision-based weed detection methods, with a particular emphasis on traditional image processing techniques and deep learning approaches for agricultural weed identification. Meanwhile, concentrated on deep learning applications in crop perception for harvesting robots. Most of these reviews either focus on a specific crop, summarize the use of particular technologies in agriculture, or examine deep learning solutions for isolated agricultural challenges.

Traditional computer vision methods for extracting manual features are costly and provide limited information, making them difficult to apply in complex agricultural environments. Deep learning can automatically learn information-rich features from data and adapt to complex agricultural environments. As both technologies continue to develop, computer vision and deep learning are playing increasingly important roles in precision agriculture and smart agriculture, much like the eyes and brain. This paper focuses on the agricultural growth management process, reviewing four aspects: crop identification and detection, crop scoring and grading, disease monitoring, and weed detection. Although deep learning and computer vision have brought revolutionary progress to agricultural intelligence, they still face numerous technical bottlenecks and practical obstacles in real-world applications.

The current urgent challenge is to achieve real-time inference in low-resource environments. The ultimate experimental objective is practical implementation to meet agricultural production needs. In actual farmland management scenarios, the lack of high-performance hardware is a common issue. Most computing devices have limited processing power, making it difficult for large-parameter models to maintain efficient inference speeds. Some farmland areas suffer from poor signal coverage [115], hindering real-time crop disease identification. Additionally, equipment such as sprayers and weeders cannot effectively support high-speed inference models, which remains a critical problem to address. For instance, in ref. [122], the proposed model achieved 85.2% mAP50 during testing. However, when deployed on mobile devices, this metric dropped to 67.4%. To resolve this issue, an increasing number of studies [86,87] have adopted more lightweight modules to optimize models, improving their deployability in practical applications. Furthermore, field operators are the primary users who need to collect and interpret precise farmland data. Excessively complex operations would increase training costs for farmers. Therefore, reducing model parameters while maintaining accuracy and lowering model complexity is essential. Ensuring reliable inference capabilities in real-world farmland environments with constrained network and computational resources represents a crucial direction for future research.

II. REVIEW SCOPE

In our extensive review of over 100 research papers sourced from esteemed scientific databases such as ScienceDirect, Web of Science, IEEE Xplore, and Scopus, we noticed a trend: while many surveys tackled the broader agricultural domain, there was a distinct gap in the literature specifically focusing on greenhouse farming. Recognizing this limited attention to greenhouse environments, we sought to make a significant contribution by narrowing our scope and offering an in-depth analysis of computer vision applications within greenhouse farming. This work emphasizes the state-of-the-art in computer vision techniques for this specialized agricultural setting. Table 1 provides a comparison between existing survey papers on deep learning-based computer vision applications in the broader agricultural domain and our niche exploration into greenhouses. With our paper, our aim was to shed light on every potential application of computer vision in greenhouse agriculture. This review is intended not only for agricultural researchers keen on understanding nuances in greenhouse setups but also for general computer vision enthusiasts curious about its specific applications in such controlled environments. Furthermore, we have pointed out the real-world impacts and challenges of scaling up these innovative solutions within greenhouses.

The main advantage of greenhouses is the ability to manipulate environmental parameters such as temperature, light intensity, moisture, and nutrient levels, adapting them to specific crop needs. This facilitates an extended growing season, improved crop quality, and efficient use of resources. However, the management and maintenance of greenhouses can be resource-intensive, and fine-tuning conditions to the optimal range for various crops can be a complex task. This is where smart greenhouses, equipped with Internet of Things (IoT) technology, come into the picture. Smart greenhouses integrate sensors and embedded controllers that collect real-time data and relay it to a cloud server. The system can then make automatic adjustments to the internal greenhouse conditions based on this data,

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minimizing human intervention. Smart greenhouses offer automatic regulation of critical factors like temperature, light, and irrigation, as well as control over other mechanical operations. This brings a new level of efficiency to farming, optimizing resource use and potentially improving crop yields.

Computer vision (CV) represents a sophisticated interdisciplinary field deeply rooted in both biological science and engineering, converging human-like perception with machine efficiency. Its core idea revolves around replicating how humans see and understand their surroundings and translating this understanding into computational models that machines can utilize. Historically, CV began as an effort to mimic human visual faculties. Early research aimed at understanding how humans perceive the world and then endowing machines with similar visual abilities. This required extensive collaboration between neuroscience to decode the human visual system and computer science to develop corresponding algorithms for machines. Groundbreaking applications such as optical character recognition (OCR) and vehicle plate detection marked the initial steps in this journey, impacting diverse areas like traffic control, law enforcement, and even retail. These achievements were furthered by the use of deep learning (DL) and neural networks, allowing for the automatic extraction of high-level features from data, reducing the need for human intervention.

III. METHODS

In the initial stages of computer vision, the primary focus was on identifying simple and basic geometric forms such as edges, curves, and corners. These early techniques were often grounded in methods like gray-level segmentation [43], which involves dividing an image into different regions based on variations in brightness or color. However, these primitive methods had significant limitations and were not robust enough to handle more complicated visual tasks where understanding and interpreting complex patterns were required. To address these limitations and enhance the interpretation of visual data, researchers sought new approaches and began to integrate artificial neural networks into computer vision systems [44]. Artificial neural networks, inspired by the human brain's interconnected neuron structure, allowed for a more sophisticated analysis of visual data [45]. Unlike the pixel-by-pixel analysis used in more rudimentary methods, neural networks provided a way for computer vision systems to analyze entire sections of an image in context, providing a more holistic understanding of the image content. This shift in approach led to substantial improvements in both performance and accuracy, enabling computer vision systems to understand and recognize more intricate patterns and shapes. Furthermore, these new methods allowed computer vision systems to analyze dynamic visual data, such as videos, enabling a higher level of interpretation that considered not only the shapes and patterns within a single frame but also how these elements changed over time [46]. The integration of neural networks marked a turning point in the field, transforming it from a discipline that could only handle rudimentary visual tasks to one that could take on complex challenges. This evolution also laid the groundwork for the modern, advanced applications of computer vision that we see today.

This was followed by other "shape from X" methods like shape from texture and shape from focus. Active range finding and model-based reconstruction, which are often used in architectural 3-D modeling, are among other methods. Designing an effective loss function for evaluating predicted 3-D point clouds against ground truth remains challenging, with options including evaluating the coverage of the ground truth object's silhouette by the projected 3-D point clouds. Deep-learning-based algorithms have recently led to significant enhancements in the performance of 3-D reconstruction systems. In summary, the world of computer vision is as complex as it is fascinating, comprising an array of techniques and tasks that together help the system understand and interact with its environment. With the rapid advancements in machine learning and artificial intelligence, we can expect to witness further evolution in these techniques, expanding the possibilities of what computer vision can achieve.

Utilizing innovative technologies to enhance agricultural processes, especially in the realm of greenhouse farming, is increasingly prevalent. embarked on an exploration using clip-type Internet of Things (IoT) cameras to monitor tomato growth in a greenhouse setting, using deep learning-based object detection to track flower blooming and immature fruit development. By integrating the flower's bloom date with temperature forecasting, their system could predict harvest dates with an average error of two days. While the clip-type design effectively addressed challenges like plant overlap in densely populated greenhouses, reliance on wired power sources and occasional occlusions posed limitations. The introduction of battery-powered IoT cameras and more adaptive positioning might enhance its applicability. In a different study, implemented a convolutional neural network (CNN)-based model to estimate growth indices for greenhouse lettuce, utilizing RGB-D data from stereo cameras.

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IV. RESULT ANALYSIS

After practical deployment of the method, improving its accuracy becomes the next major challenge. Designing universally generalizable models for multi-scale dynamic targets thus represents a high-priority technical challenge. For crop identification and detection, the varying shapes of crops make multi-scale target detection particularly difficult. The system must simultaneously detect targets ranging from millimeter-scale objects (e.g., pollen) to meter-scale structures (e.g., fruit tree canopies), while accounting for morphological changes throughout the growth cycle. Crops like grapes present additional challenges with severe overlapping and occlusion issues. In disease monitoring, visible damage on crop surfaces varies significantly in size. However, many diseases cause extremely subtle damage that is difficult to detect in early stages. The weak initial symptoms and tiny detection targets constitute major obstacles in disease surveillance. Studies such as focus on extracting more advanced and diverse features. These high-level fused features typically incorporate both global and local crop information, enabling better identification of diseased areas. For pest monitoring, the small size and high mobility of target insects create substantial detection challenges. When processing small insect features, it is crucial to avoid feature loss caused by excessive extraction spans, which may lead to missed detections. compared multiple models and expanded the number of recognizable pest categories to nine, yet universal generalizability remained unattainable. Weed detection faces similar issues. Weeds are typically small, morphologically diverse, and sometimes resemble crops, factors that significantly increase the difficulty of accurate identification. Studies like have proposed using multi-scale convolution or attention layer mechanisms to enhance feature extraction and focus on weeds, thereby improving detection accuracy and generalizability. However, misidentification still occurs in heavily occluded environments, where non-weed plants may be incorrectly classified. Developing models capable of handling multi-scale targets while improving generalizability remains a critical challenge.

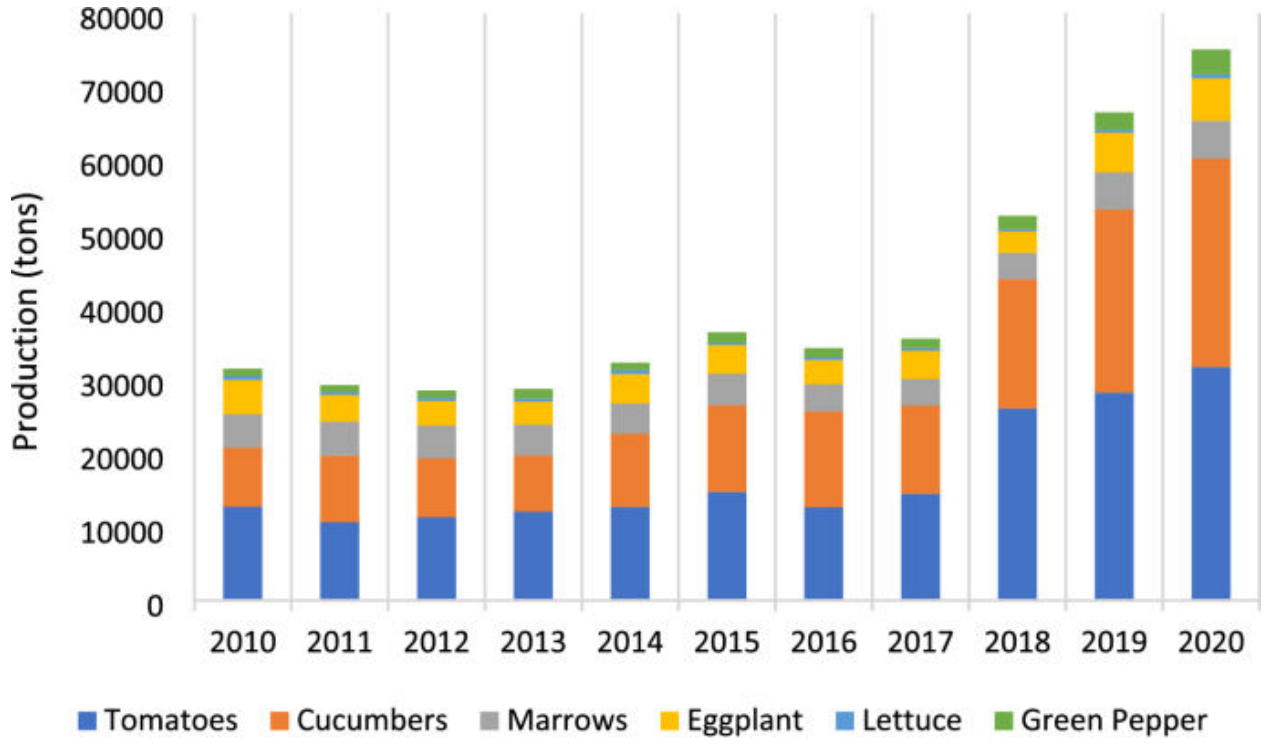


Fig 2: Smart greenhouses as the path towards precision agriculture

Agricultural field environments are complex, and dynamic environmental interference affects model accuracy. In real-world scenarios, issues such as target overlap, occlusion, and background interference persist. These factors, along with variations in lighting, temperature, humidity, and background conditions, influence the input data acquisition for models. Consequently, there are discrepancies between practical application results and laboratory test performance, indicating a need for improved method adaptability. Studies such as have enhanced detection models to achieve better

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accuracy in complex environments, though these improvements remain condition-specific. To strengthen model stability in challenging conditions, research can also focus on input data optimization. Acquiring high-quality image data and constructing comprehensive datasets that encompass diverse real-world scenarios represent a growing trend for improving model precision. As discussed in Section 2, integrating technologies like structured-light cameras and infrared spectroscopy can effectively enhance data quality. However, the use of such high-performance equipment increases costs significantly. To address this, some studies [82] employ data augmentation techniques to improve data quality and testing accuracy without requiring expensive hardware. This approach balances performance and cost-effectiveness while maintaining model reliability in variable agricultural environments. Future work should continue exploring robust data acquisition and processing methods to bridge the gap between controlled testing and real-world deployment.

V. CONCLUSION

However, the application of deep learning and computer vision in agriculture also faces numerous challenges. Scarce and expensive labeled data constrain model generalization capabilities, and the early detection of millimeter-sized pests and diseases remains a technical challenge. Algorithms need to be deployed on actual devices to ensure the practical implementation of the technology, but hardware investments result in prohibitively high costs. Additionally, complex real-world environments limit the effectiveness of algorithms and hardware. Despite these challenges, the field still holds significant potential for future development. First, specialized large-scale models for agriculture should be developed, leveraging pre-training with massive datasets to enhance transfer learning capabilities and improve model generalization. Second, novel sensing technologies, deep learning techniques, and agriculture should be more comprehensively integrated, such as quantum sensing and nano-imaging technologies, as well as various more efficient attention mechanisms. Finally, experiments and production should progress together. By designing lightweight models to lower application barriers, research findings can be more widely adopted and applied. It is foreseeable that when technological maturity aligns with industrial demand, agriculture will enter an era of smart agriculture, where the entire process from sowing to harvest will be driven by autonomous decision-making. This leap in production efficiency is a crucial safeguard for food security and sustainable development—and a top priority for human societal progress.

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