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Deep Learning And Multi-Model Fusion For Crop Maturity Prediction: A Review

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Abstract: Crop maturity prediction is a critical aspect of precision agriculture, enabling farmers to optimize harvest timing, reduce losses, and improve yield quality. Re- cent advancements in deep learning (DL) and multi-model fusion (MMF) techniques have shown significant promise in enhancing the accuracy and robustness of crop maturity prediction models. This paper provides a comprehensive review of state- of-the-art DL and MMF approaches applied to crop maturity prediction, following the PRISMA guidelines. We systematically analyze the latest research, identify key challenges, and discuss future directions. The review covers methodologies, data- sets, performance metrics, and comparative analyses of various models, providing a holistic understanding of the current landscape and potential advancements in this field. Multi-model fusion, which combines data from various sources such as remote sensing, meteorological data, soil properties, and genomics, has emerged as a powerful approach in crop maturity prediction. By integrating complementary in- formation from different modalities, these models can capture complex patterns and relationships that single-model approaches might miss. This review explores the cur- rent state of research in this domain, highlighting key methodologies, architectures, and applications.

***Index Terms* -** deep learning, computer vison, multi-model fusion, crop maturity, prediction, precision agriculture, artificial intelligence, image classification, image segmentation, object detection.

1. INTRODUCTION

Crop maturity prediction is a critical aspect of modern agriculture, enabling farmers and policymakers to make informed decisions regarding harvest planning, resource allocation, and market strategies. With the advent of deep learning and multi-model fusion techniques, the accuracy and reliability of crop maturity prediction models have significantly improved. This review explores the current state of research in this domain, highlighting key methodologies, architectures, and applications. However, smallholder farmers con- front a myriad of obstacles, including limited access to advanced technology, resource constraints, and susceptibility to environmental pressures and market fluctuations [1]. Over recent years, the integration of digital technologies, particularly deep learning-assisted computer vision techniques, has emerged as a promising avenue to address these challenges and enhance productivity, efficiency, and sustainability in farming [2].

Deep learning, a subset of machine learning methodologies inspired by the structure and functioning of the human brain, has demonstrated remarkable capabilities in analyzing intricate datasets, identifying patterns, and making predictions [3]. When coupled with computer vision, which enables machines to interpret and comprehend visual information from images or videos, deep learning algorithms have shown significant potential in revolutionizing various facets of agriculture, encompassing crop monitoring, pest management, yield estimation, and decision support systems [4].

Multi-model fusion, which combines data from various sources such as remote sensing, meteorological data, soil properties, and genomics, has emerged as a powerful approach in crop maturity prediction. By integrating complementary information from different modalities, these models can capture complex patterns and relationships that single- model approaches might miss [5]. For instance, remote sensing data provides spatial and temporal information about crop health and growth, while meteorological data offers insights into environmental conditions that influence crop development [6]

In light of these considerations, this paper seeks to offer a comprehensive review of the latest research literature on deep learning-assisted computer vision techniques tailored for crop maturity prediction. By synthesizing existing knowledge, identifying key advancements, and elucidating potential avenues for future research and development, this review endeavors to contribute to a nuanced understanding of the capabilities, challenges, and opportunities associated with the application of deep learning in farming practices.

2. METHODOLOGY

2.1 Review protocol

The process of conducting a review involves three main steps; planning, conducting and reporting the outcomes. Initially, the necessity for writing the review is established, and it is noted that no existing reviews address the maturity prediction entangled with multi-modal input data. Subsequently, the research questions, relevant keywords, and publication databases are identified. During the review process, all databases are searched to identify pertinent studies. Criteria for selecting primary studies and synthesizing data are then defined. In the final reporting phase, the specified dissemination mechanism is implemented, the main report is formatted, and the gathered information is evaluated.

2.2 Research questions

This study seeks to provide a comprehensive understanding of research related to environmental parameter prediction in agricultural facilities, examining the topic through four specific research questions outlined as follows:

RQ1: What are key deep learning architectures and techniques currently being utilized for crop maturity prediction?

RQ2: How does multi-model fusion enhance the accuracy and robustness of crop maturity prediction?

RQ3: What are the major challenges and limitations in applying deep learning and multi- model fusion for crop maturity prediction?

2.3 Search strategy

A systematic approach was employed to narrow down the literature to studies relevant to the scope of the Systematic Literature Review (SLR). To improve the standardization of the search process, the search string was simplified and unified to serve as a guide for future researchers. The finalized search string is as follows: ((“Machine Learning” OR “Deep Learning”) AND (“Crop Maturity Estimation” OR “Crop Maturity Prediction”) AND (“Smart Agriculture” OR “Precision Agriculture”)). This search string was applied to the abstract, title, and keyword fields, resulting in the retrieval of 26 and 30 studies from Google Scholar, Web of Science respectively.

2.4 Selection criteria

The retrieved literature was evaluated based on predefined exclusion criteria to eliminate studies that were not aligned with the research topic. The exclusion criteria (EC) applied were as follows:

EC 1: The publication does not address the prediction of environmental parameters in agricultural facilities.

EC 2: The publication is a duplicate or has been retrieved from another database.

EC 3: The publication is a survey or review paper.

EC 4: The full text of the study is unavailable.

3. Results

3.1 Deep learning in precision agriculture

In the recent decade, Artificial Intelligence (AI) gathered attention across the world and changes the way of living of human beings. AI is being used in every discipline such as medical science, automobile industry, entertainment industry, space and aeronautics etc. Deep learning (DL) is a collection of techniques from artificial neural network (ANN), which is a branch of machine learning. ANNs are modelled on the human brain; there are nodes linked to each other that pass information to each other [7]. Depending on the nature of the problem and neuron topology, proposed neural network consists of multiple level of processing layer to obtain the higher level of abstraction and how accurately credits to be assigned throughout the lower level to higher level. The artificial neuron is basic building block compute the summation of assigned credits and proposed activation function performed; activation function decides whether the perceptron to be fired or not. There are mainly three important reasons for the booming of deep learning today: the dramatically increased chip processing abilities (e.g. GPU units), the significantly lowered cost of computing hardware, and the considerable advances in the machine learning algorithms: Convolutional Neural Networks (CNNs) deep learning algorithm notably used by the researchers in various disciplines composed of multiple layers, pooling layers and fully connected layers which has resulted into many breakthroughs in speech recognition, face recognition, natural language processing, computer vision and so on [8].

Recurrent Neural Networks (RNNs)RNNs belongs to the class of ANN, mines the information of past and current time period to mimic as human behavior use persisted long and short past memory information to make decisions. RNNs has model predictive networks to predict the information with high temporal dependencies [9]. Generative Adversarial Networks (GANs)GANs neural network fathered by Ian Goodfellow, in 2014. It is an unsupervised algorithm comprises of two neural network as a discriminator (similar to binary classifier) and generative, simultaneously [10].

3.1.1 Applications deep learning agriculture

Deep Learning (DL) has emerged as a transformative technology with profound applications across various sectors, including agriculture. Its capacity to analyze large datasets, identify patterns, and make predictions has significantly impacted agriculture, enhancing efficiency, productivity, and sustainability across the entire crop production cycle, from preharvest to postharvest stages.

Preharvest Phase: Crop Disease Detection: DL techniques, such as convolutional neural networks (CNNs), have been deployed for early detection of crop diseases based on image analysis of plant symptoms [11].

Crop Yield Prediction: DL models are utilized to predict crop yields based on di- verse factors including weather patterns, soil conditions, and historical yield data, aiding farmers in decision-making processes [12].

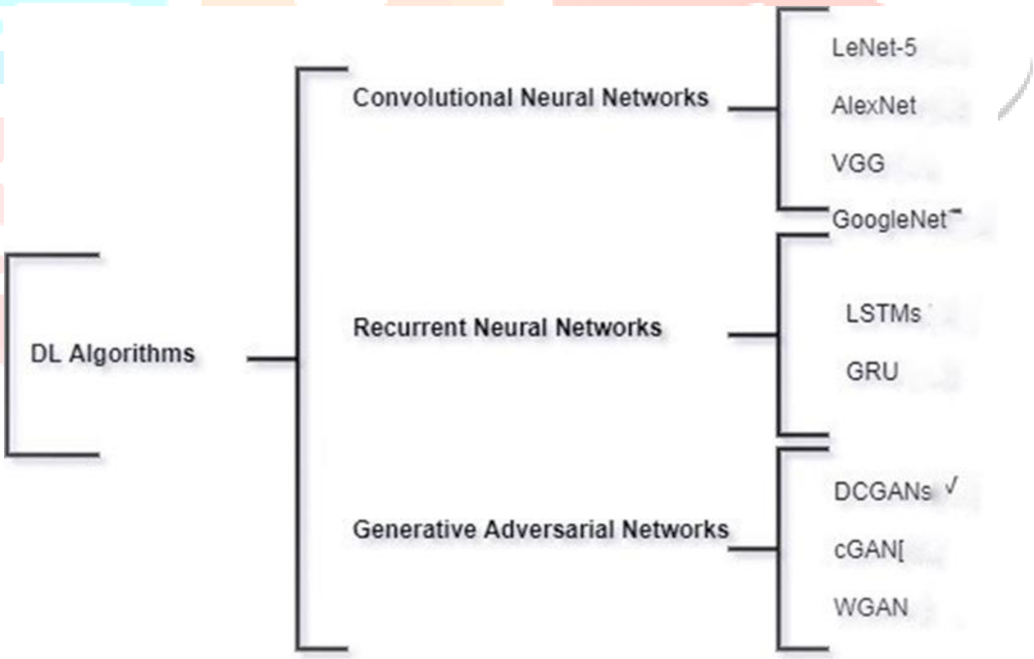

Figure 1: Variants of deep learning algorithms.

Harvest Phase:

Weed Detection and Management: DL algorithms are employed for weed detection and classification in real-time, facilitating precision agriculture practices and reducing the need for herbicides [13].

Harvest Automation: DL-based vision systems are used to automate harvesting processes by identifying ripe fruits or vegetables, enabling efficient harvesting operations [14].

Postharvest Phase:

Quality Assessment and Sorting: DL techniques are applied for quality assessment and sorting of harvested produce based on various parameters such as size, color, and defects, ensuring only high-quality produce reaches the market [15]. DL technologies offer immense potential in revolutionizing agriculture practices throughout the crop production cycle. By leveraging advanced algorithms and computational power, DL facilitates better decision-making, enhances productivity, reduces resource wastage, and contributes to sustainable agricultural practices.

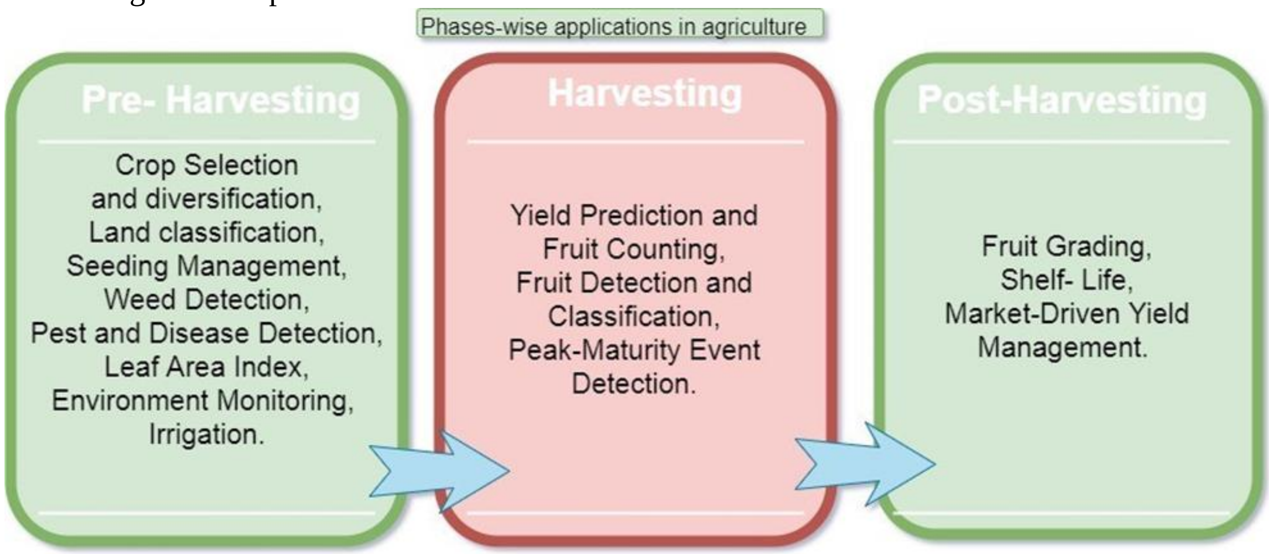

Figure 2: Applications of deep learning in agriculture.

• **Sensors**: Traditional sensors primarily measure weather conditions or fundamental soil properties. However, ongoing advancements are leading to the development of new sensor types, capable of monitoring nutrients or providing more precise assessments of plants and livestock. Additionally, there is emerging research focusing on in-plant sensing technologies.

• **IoT** (Internet of Things): The integration of small, cost-effective, and disposable sensors within IoT platforms facilitates real-time monitoring and enables cloud or edge computing. This integration enhances visibility and traceability throughout the food supply chain. For instance, if perishable goods surpass temperature thresholds during transportation, such deviations can be promptly recorded and flagged in real-time. There is also an increasing demand for transparency regarding the origin of food products.

• **Imagery**: Remote sensing, a longstanding practice in agriculture involving the ana- lysis of satellite data images, has seen recent developments. These include utilizing low Earth orbit (LEO) satellites to access images more frequently and employing higher-resolution imagery from drones for on-demand monitoring of crop health, pest outbreaks, and disease occurrences.

• **Blockchain**: The utilization of secure blockchain technology ensures traceability and facilitates smart contracts, providing assurance to sellers, buyers, and consumers regarding the authenticity and integrity of information related to the sourcing and transit of food products and shipments.

• **Artificial intelligence** (AI): With the availability of vast quantities of data with im- proved resolution, timeliness, and quality, there is a growing need for advanced techniques in distributed computing to process this data effectively and derive action-able insights. AI, including machine learning (ML), is already being applied in various agricultural tasks such as crop prediction and chatbots, with ongoing advancement promising even more sophisticated applications. Augmented intelligence holds potential for supporting decision-making in precision agriculture systems in the near future.

• **Computer vision**: Advancements in algorithms are enhancing the analysis of abundant imagery and photographs. For instance, AI models can swiftly identify specific plant pests and diseases from a photograph of a leaf, enabling real-time treatment recommendations. Additionally, computer vision algorithms can automatically ex- tract farm field boundaries from satellite images.

3.1.2 Precision agriculture research and development

In agricultural research and development, particularly within plant science, plant phenotyping involves a range of methodologies and protocols aimed at accurately assessing various aspects of plant growth, structure, and composition across different scales. The advent of next-generation sequencing technology has significantly accelerated functional genomics, allowing for the identification of key genes and agronomic traits. Understanding the interplay between genetics and the environment (GxE) through phenotyping is crucial for crop breeding efforts [16].

Recent advancements in digital technology have facilitated swift phenotyping. Technologies such as high-resolution multi-spectral imaging, drone imagery, in-ground sensors, and data platforms enable precise measurement, analysis, and the generation of digital representations. However, the adoption of such solutions remains limited in Low and Middle-Income Countries (LMICs). Further development is necessary, particularly in enhancing below-ground measurement techniques for root structures [17].

3.1.3 Computer vision techniques for smart farming

A lot of the cutting-edge technology utilized in agriculture is a result of AI. Contemporary technologies such as computer vision (CV), Internet of Things (IoTs), edge computing, machine learning (ML), and DL can be utilized to create intelligent and automated models in the agricultural industry. The well-known phrase "AI is accelerating and data is new fuel" Throughout the three main stages of the agricultural process—pre-harvesting, harvesting, and post-harvesting—a lack of proper information resulted in enormous losses. Every phase contains a number of smaller tasks that must be completed thoughtfully and strategically in order to minimize additional expenses and limit the potential for financial losses.

3.2 Influence of multi modalities

Multimodal approaches in agriculture bring together a diverse range of methods and technologies to boost productivity, sustainability, and resilience in farming practices. These approaches merge traditional agricultural techniques with cutting-edge innovations like precision agriculture, biotechnology, and advanced data analytics to optimize resource utilization and enhance crop yields. By integrating multiple strategies, farmers can effectively tackle challenges such as climate change, pest control, and soil degradation, while also ensuring food security for an increasingly expanding global population [18].

Four Rights for PA with respect to proposed multi-modal maturity assessment approach:

- **Right Input**: Multi-modal input data, Spatial-temporal, spectral-temporal, environmental. RGB, RGB-D, NIR, temperature, moisture content, GDDs.
- **Right Place** (scale): Maturity period is short-temporal period of approx. 30 days, In terms of scale, panicle-level scale to be chosen. Spaceborne and airborne remote sensing has spatial-temporal trade-off and covers large scale. Satellite not satisfying the demand of precise crop monitoring. Harvesting, crop monitoring usually done in short time frame to take quick action).
- **Right Time**: Near-real time and comprehensive assessment.
- **Right management practice**: Multi-modal maturity assessment approach for the estimation of harvest events.

3.3 Multi-modal and DL synergy

To overcome the constraints of RGB cameras, multi-modal sensors are utilized to improve their perceptual capabilities; advantages and disadvantages classified as in fig.3. This enhancement is generally carried out in two key dimensions: spatial and spectral. This paper examines deep learning-based techniques that take advantage of multimodal sensors within these dimensions [19]. For the spatial dimension, the discussion centers on two sensor pairings. RGB+depth and RGB+LiDAR. For the spectral dimension, the focus is on the integration of RGB and infrared cameras. For each sensor combination, three critical elements are analyzed: datasets, fusion techniques, and practical applications.

The integration of multiple sensors through data fusion is a critical area of research, with significant implications across various fields such as robotics, healthcare, and smart manufacturing. This process involves combining data from different sensors to improve the accuracy, reliability, and efficiency of the information obtained. The three critical elements in sensor combination: data sets, fusion techniques, and practical applications are essential to understand and advance this technology. Each element plays a vital role in the development and implementation of effective sensor fusion systems.

Modalities	Advantages	Limitations
RGB	low cost, high resolution	prone to be affected by lighting condition and bad weather
LiDAR	3D perception, less affected by lighting condition and bad weather	high cost, low resolution
Depth	3D perception, high resolution, relatively low cost	limited range and FOV, contain noise and holes
NIR	near-infrared spectrum perception, less affected by lighting condition and bad weather	Requires specific hardware and may have higher costs, lacking color information
FIR/Thermal	Captures thermal radiation and provides temperature information	Specialized and relatively expensive, low spatial resolution, lacking color information
RGB+X	levarage the advantage of RGB and X	higher cost, higher computation cost

Figure 3: Numerous merits and demerits of different modalities.

3.3.1 Datasets

Diversity and Volume: The datasets used in sensor fusion are often large and heterogeneous, comprising data from various sensor types such as LiDAR, cameras, and IMUs. For instance, in autonomous navigation, datasets include laser and vision-based sensor data to enhance perception and decision-making capabilities [20].

Application-Specific Datasets: Different applications require specific datasets. For ex- ample, in healthcare, datasets might include physiological signals from wearable sensors, while in smart manufacturing, they might involve machine and environmental data [21]. Benchmarking and Evaluation: Datasets like Amazon Reviews and MovieLens are used to evaluate fusion techniques, highlighting the importance of choosing the right dataset for testing and validation [22].

3.3.2 Fusion Techniques

Algorithmic Approaches: Various fusion techniques are employed, including Kalman filters, Bayesian networks, and deep learning models. These methods help in reducing noise and improving data accuracy [21] [23].

Multimodal Fusion: Techniques such as early and late fusion are used to combine data from different modalities, which is crucial for applications like robotics and autonomous systems [22].

AI and Machine Learning: The integration of AI, particularly deep learning, has enhanced the capabilities of sensor fusion by enabling more sophisticated data processing and ana- lysis [24].

3.3.3 Practical applications of multi-modal systems

Integration of multimodal technologies in agriculture has led to significant advancements in precision farming, enhancing productivity, efficiency, and sustainability. Multimodal systems leverage diverse data sources and technologies, such as remote sensing, IoT, ma- chine learning, and robotics, to provide comprehensive insights into agricultural processes. These systems enable precise monitoring and management of crops, livestock, and environmental conditions, ultimately improving yield and reducing resource wastage. Below are some practical applications of multimodal technologies in agriculture, as derived from the provided research papers.

Crop Monitoring and Management:

Remote Sensing and Machine Learning: Multimodal systems utilize satellite and UAV imagery combined with machine learning to monitor crop health, predict yields, and manage resources efficiently. For instance, high-resolution satellite images are used to assess plant responses and manage spatial variability in vineyards, enhancing resource use efficiency and crop quality under climate change conditions [25].

Data Fusion in Greenhouses: In greenhouse environments, multimodal data fusion from various sensors (e.g., soil moisture, temperature) enables precise environmental monitoring and management, improving crop growth conditions and yield [26].

Precision Livestock Farming

Behavioral Monitoring: Multimodal vision frameworks, such as AnimalFormer, analyze livestock behavior through video data, providing insights into activity patterns, health assessments, and welfare optimization without invasive tagging [27].

Autonomous Agricultural Robotics

Localization and Mapping: The CitrusFarm dataset exemplifies the use of multimodal sensory data for developing autonomous robots in agriculture. These robots can perform tasks like localization, mapping, and crop monitoring, enhancing efficiency in citrus tree farms [28].

Harvesting Process Optimization

Task Assignment and Coordination: Multimodal systems facilitate real-time task assignment and coordination among agricultural machinery during harvesting. This includes using cloud-based platforms for dynamic replanning and communication with drivers, ensuring efficient and uninterrupted harvesting operations [29].

While multimodal technologies offer numerous benefits, their implementation in agriculture faces challenges such as high initial costs, data management complexities, and the need for skilled personnel. Additionally, the integration of these technologies into traditional farming practices requires careful consideration of local conditions and farmer acceptance. Despite these challenges, the potential for improved efficiency and sustainability makes multimodal systems a promising avenue for the future of agriculture.

4. Challenges Of Crop Maturity Assessment Parameters

Despite its significant benefits, remote sensing encounters several hurdles when applied to small-scale precision agriculture. These challenges stem from limitations in spatial resolution, cost-effectiveness, practicality, and complexity of data interpretation.

Spatial Resolution Constraints: Remote sensing predominantly relies on satellite or aerial imagery, often with limited spatial resolution. This limitation means that such imagery may not capture the fine details required for precise analysis and management of small-scale agricultural plots [30].

Variability in Small Plots: Small-scale farms tend to exhibit considerable spatial heterogeneity concerning factors like crop types, soil characteristics, and management practices. Remote sensing methods may struggle to accurately capture this variability, leading to less accurate recommendations for precision agriculture interventions [31].

Financial Considerations: Acquiring, processing, and interpreting high-resolution remote sensing data can be costly. For small-scale farmers with limited resources, the cost may outweigh the benefits, especially when alternative, more accessible methods are available [30].

Complex Data Analysis: Making sense of remote sensing data often necessitates specialized expertise in areas such as image processing, machine learning, and agronomy. Small-scale farmers may lack the necessary technical knowledge or resources to interpret the complex information provided by remote sensing platforms effectively [32].

Logistical Hurdles: Implementing remote sensing solutions in small-scale agriculture settings may pose logistical challenges related to data transmission, infrastructure requirements, and field validation. These challenges can impede the adoption and scalability of remote sensing technologies among smallholder farmers [33].

While remote sensing holds immense promise for agricultural monitoring and management, its application in small-scale precision agriculture is hindered by limitations in spatial resolution, cost considerations, data interpretation complexity, and logistical obstacles. Addressing these challenges is crucial to enhance the accessibility and effectiveness of remote sensing technologies for smallholder farmers.

4.1 Recent developments in computer vison for precision agriculture

In recent years, significant advancements have been made in applying deep learning (DL) methods to small-scale computer vision challenges. These breakthroughs have led to the creation of more efficient, precise, and resource-friendly models tailored specifically for tasks across diverse domains:

- **Compact Architectures**: Researchers have concentrated on designing streamlined DL architectures suitable for deployment on devices with limited resources. Models like MobileNetV3 [34] and EfficientNet [35] exemplify this trend, offering a balance between accuracy and computational efficiency.
- **Transfer Learning Approaches**: Transfer learning has emerged as a potent technique for adapting pre-trained DL models to small-scale computer vision tasks. Methods such as fine-tuning and feature extraction from pre-trained models like VGG, Res- Net, or MobileNet have shown significant performance enhancements in domains with sparse training data [36].
- **Few-Shot Learning**: To address the challenge of limited annotated data, researchers have explored few-shot learning methods, enabling DL models to learn from a small number of labeled examples. Meta-

learning techniques such as model-agnostic meta- learning (MAML) [37] have demonstrated efficacy in rapidly adapting DL models to new tasks with minimal training data.

- **Integration of Attention Mechanisms**: Incorporating attention mechanisms into DL architectures has improved model interpretability and performance in small-scale computer vision tasks. Models equipped with attention mechanisms can selectively focus on pertinent regions of input data, enhancing their ability to handle complex and varied inputs effectively [38].
- **Domain-Specific Optimization**: Customizing DL models to specific application do- mains has resulted in significant performance improvements in small-scale computer vision tasks. Domain-specific optimizations may involve architectural adjustments, customized loss functions, or tailored data augmentation strategies adapted to the characteristics of the target problem [39].

In summary, recent strides in deep learning research for small-scale computer vision techniques have led to the creation of more efficient, accurate, and adaptable models. These advancements hold great potential for empowering applications across various domains, including healthcare, agriculture, and robotics.

5. Discussion

The incorporation of deep learning (DL) and multi-model fusion (MMF) methods into crop maturity prediction marks a notable leap forward in precision agriculture, as emphasized in this review. The findings reveal that these technologies can substantially improve the accuracy and reliability of predictive models, which is vital for optimizing harvest schedules and enhancing crop quality. The review highlights the critical role of leveraging diverse data sources—such as remote sensing, meteorological data, soil characteristics, and genomics—to build a comprehensive understanding of crop maturity dynamics. By integrating these varied data types, researchers can uncover intricate patterns and relationships that might be missed by single-model approaches, offering a more holistic perspective on crop development.

Nevertheless, the review also outlines several challenges that need to be overcome to fully harness the potential of DL and MMF in agriculture. A key challenge is the requirement for more diverse and representative datasets that cover a broad spectrum of agricultural conditions. Such diversity is crucial for training models that can perform well across different environments and crop varieties. Furthermore, the integration of multi-modal data introduces its own complexities, as researchers must devise methods to effectively merge and analyze these disparate data sources.

Additionally, the review stresses the importance of improving model interpretability. Since deep learning models often function as "black boxes," understanding the reasoning behind their predictions is essential for gaining farmers' trust and encouraging the adoption of these technologies in practical applications. By enhancing interpretability, re- searchers can offer actionable insights that enable farmers to make well-informed decisions based on model outputs.

The discussion also highlights opportunities for future research to explore innovative strategies for better integrating multi-modal data and enhancing the performance of predictive models. This could include developing hybrid models that combine the strengths of different algorithms or applying transfer learning techniques to adapt models trained in one context to another. Such advancements could greatly expand the applicability of crop maturity prediction models across diverse agricultural settings.

6. Conclusion

Crop maturity prediction plays in the realm of precision agriculture, emphasizing its im- portance in optimizing harvest timing, reducing losses, and enhancing yield quality, which are essential for sustainable agricultural practices and food security. The authors high- light that recent advancements in deep learning (DL) and multi-model fusion (MMF) techniques have significantly improved the accuracy and robustness of crop maturity pre- diction models, showcasing how these technological innovations facilitate the integration of diverse data sources, leading to more reliable predictions. The review meticulously analyzes the latest research methodologies, datasets, performance metrics, and comparative analyses of various models, providing a comprehensive understanding of the current landscape and potential future advancements in crop maturity prediction. Furthermore, the authors identify several challenges that need to be addressed, such as the necessity for more diverse datasets, the integration of various data types—including remote sensing and soil properties—and the development of models that can generalize well across different agricultural conditions. These challenges underscore the complexity of the agricultural environment and the need for tailored solutions that can adapt to varying conditions. Future research should focus on enhancing the integration of multi-modal data sources and improving model interpretability, which will not only boost prediction accuracy but also provide farmers with actionable insights for better decision-making.

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