Integrating Plant Phenomics and Large Language Models for Precision Agriculture: A Survey

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Abstract

This survey paper explores the integration of plant phenomics, Large Language Models (LLMs), and Multimodal Large Models (MLLMs) within precision agriculture, emphasizing their collective potential to enhance agricultural productivity and sustainability. By synthesizing phenotypic, genotypic, and environmental data, these advanced computational tools facilitate real-time, data-driven decision-making processes. High-throughput phenotyping technologies, coupled with AI-driven analytics, enable rapid and precise assessments of plant traits, addressing traditional phenotyping limitations. LLMs automate data synthesis and decision-making, although challenges such as biases and computational demands persist. MLLMs further expand AI capabilities by integrating diverse data types, exemplified by models like MA-LMM, which enhance agricultural decision-making through comprehensive data analysis. The survey highlights the role of AI in optimizing resource use and improving crop monitoring through IoT and remote sensing technologies. Despite the transformative potential of these technologies, ethical and practical challenges, including data biases and environmental impacts, necessitate robust frameworks for ethical AI deployment. Future research directions include optimizing data processing systems, enhancing model efficiency, and integrating phenomics with other omics technologies to advance crop breeding and sustainability. By addressing these challenges, AI integration in agriculture can be optimized to support more resilient and sustainable agricultural systems.

1 Introduction

1.1 Contextualizing Plant Phenomics and AI

The integration of plant phenomics with artificial intelligence (AI) is transforming agriculture by leveraging advanced computational tools to enhance productivity and sustainability. High-throughput phenotyping accelerates crop breeding through rapid and precise trait assessments across large populations, overcoming the limitations of traditional, labor-intensive methods [1]. The wealth of genotypic data from next-generation sequencing further enriches the resources for investigating and improving complex traits.

Large Language Models (LLMs) automate data processing, enhancing decision-making in complex, rule-based environments [2]. However, their deployment in agriculture poses risks due to generative biases and the potential for harmful outputs [3], necessitating robust frameworks and benchmarks for reliability [4].

Multimodal large language models (MLLMs) expand AI capabilities in agriculture by integrating diverse data types for comprehensive analysis, as demonstrated by the Memory-Augmented Large Multimodal Model (MA-LMM), which enhances long-term video understanding in agricultural contexts [5]. As AI technologies evolve, their role in precision agriculture is expected to grow, improving decision-making and promoting sustainable practices. The synergy of plant phenomics and AI enhances the accuracy of phenotypic data collection and analysis, facilitating the development

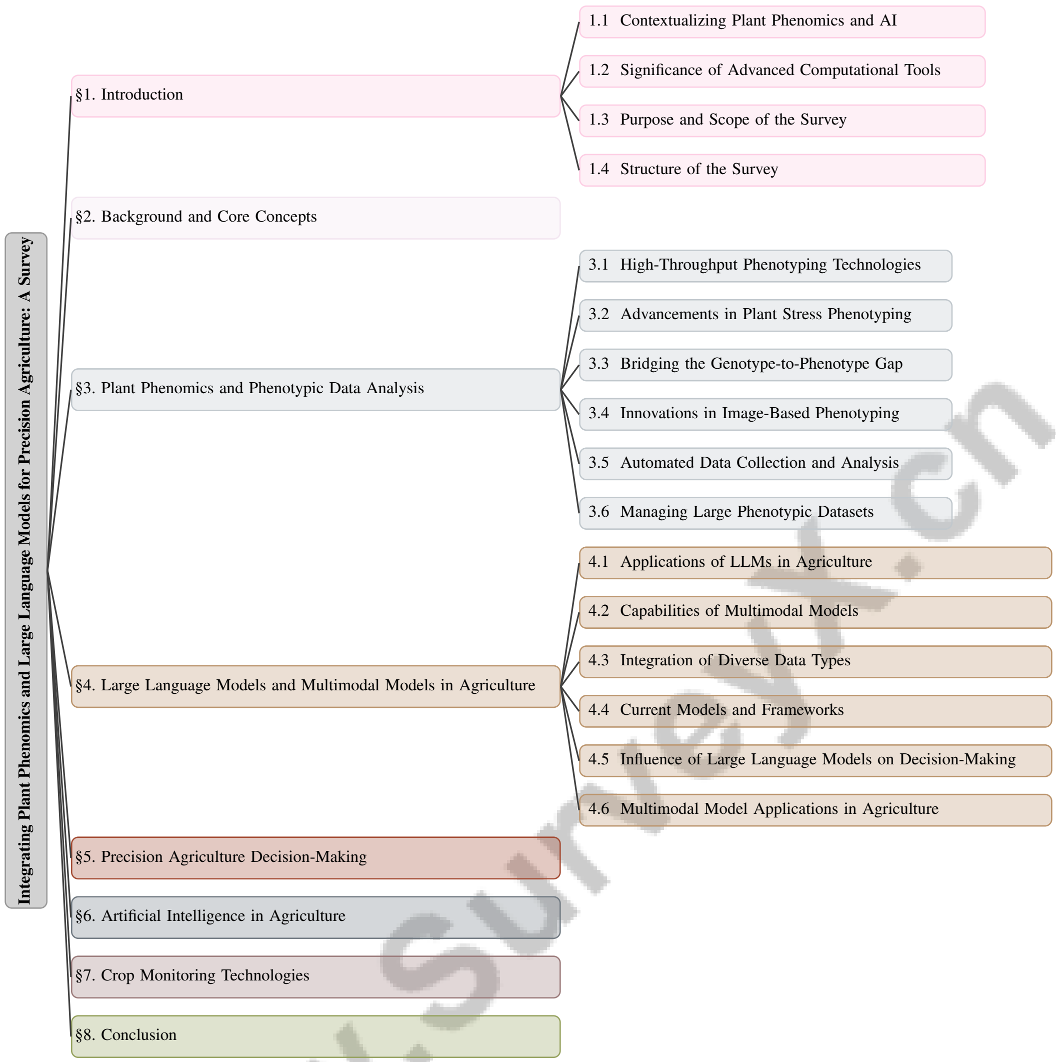


Figure 1: chapter structure

of high-throughput systems that capture complex traits under varying environmental conditions. This integration promises to boost agricultural productivity and support sustainable farming by enabling precise stress identification and efficient plant population screening [6, 7, 8, 9].

1.2 Significance of Advanced Computational Tools

Advanced computational tools, particularly LLMs, are pivotal in revolutionizing agricultural practices through the automation of data synthesis and analysis encompassing phenotypic, genotypic, and environmental information. Evaluations reveal their significant potential in educational settings, demonstrating capabilities in processing complex data structures and facilitating informed decision-making [2]. However, challenges persist, including the probabilistic nature of their outputs and risks of misinformation, particularly in climate data contexts [10].

LLMs' multilingual capabilities enhance their applicability in global agriculture by facilitating the integration and analysis of diverse linguistic datasets, promoting cross-cultural practices and collaboration among stakeholders. They streamline information retrieval and data insight generation, crucial for adapting agricultural strategies to varying cultural contexts [11, 12, 13]. This is especially beneficial in regions with limited linguistic resources, where coherent narrative synthesis from tabular data can significantly enhance decision-making processes.

Ethical concerns surrounding LLM deployment, including biases in training data, risks of generating misleading content, and the complexities of accountability and transparency, warrant thorough examination. Addressing these challenges is essential for mitigating biases and ensuring responsible integration of LLMs in agriculture, thus safeguarding against potential misuses in information dissemination and decision-making [14, 11, 15, 16]. Robust ethical and regulatory frameworks are necessary to reconcile LLM advancements with essential standards, addressing challenges such as accountability, bias reduction, and transparency while aligning with societal values [17, 14, 18, 12, 19].

In scenarios with scarce real-world data, synthetic data generation becomes a vital strategy, providing necessary data for training and refining LLMs. As agricultural systems increasingly rely on computational tools, developing regulatory frameworks that keep pace with technological advancements is imperative.

1.3 Purpose and Scope of the Survey

This survey explores the integration of plant phenomics with LLMs and MLLMs within precision agriculture, addressing critical challenges posed by global population growth and climate change on food production. It focuses on methodologies and technologies utilized in plant phenotyping and phenomics, specifically advancements in high-throughput phenotyping techniques such as imaging technologies, while excluding traditional labor-intensive methods [20, 9].

The analysis extends to LLM applications across various domains, including finance, multilingual contexts, biomedical fields, and code generation [21]. It examines four key aspects of LLMs: pre-training, adaptation tuning, utilization, and capacity evaluation, particularly models with over 10 billion parameters [22]. Additionally, it highlights eight surprising claims about LLMs, focusing on their capabilities, interpretability, and challenges in behavior direction [23].

The survey investigates LLMs' roles in academic writing, education, and programming, while excluding detailed technical specifications or programming tutorials [15]. It encompasses CMR methodologies using LLMs, applications across modalities (text, image, audio), and integration challenges [24]. A data-centric perspective emphasizes the critical role of data in model performance [25].

Furthermore, the survey aims to standardize AI concepts, methodologies, and interrelations, addressing knowledge gaps and providing a comprehensive framework for AI researchers, developers, and educators [26]. It explores transparency in LLM systems, identifying challenges and proposing solutions for effective integration [18]. The survey also consolidates techniques for mitigating hallucination in LLMs, providing a systematic taxonomy for these methods [27].

Lastly, the survey incorporates stages of systematic reviews that can be automated using LLMs, such as publication searches, data extraction, and drafting [19]. By synthesizing these elements, the survey illuminates the potential of integrating advanced computational tools with agricultural practices to enhance productivity and sustainability [28].

1.4 Structure of the Survey

This survey is systematically organized into several key sections to comprehensively explore the integration of plant phenomics with LLMs and MLLMs in precision agriculture. The paper begins with an **Introduction**, contextualizing the intersection of plant phenomics and AI technologies and highlighting their significance in enhancing agricultural productivity and sustainability.

Following the introduction, the **Background and Core Concepts** section delves into foundational aspects of plant phenomics, LLMs, multimodal models, and precision agriculture, elucidating their interconnections and relevance. This is succeeded by a detailed examination of **Plant Phenomics and Phenotypic Data Analysis**, exploring advancements in high-throughput phenotyping technologies, plant stress phenotyping, and innovations in image-based phenotyping, alongside challenges and solutions in managing large datasets.

The survey transitions to the **Large Language Models and Multimodal Models in Agriculture** section, investigating applications of these models in agriculture, focusing on their capabilities in processing diverse data types and influencing decision-making processes. This is complemented by the **Precision Agriculture Decision-Making** section, scrutinizing the role of AI and computational tools in optimizing resource use and enhancing decision-making workflows.

Subsequently, the **Artificial Intelligence in Agriculture** section provides an overarching view of AI applications beyond phenomics and LLMs, addressing ethical and practical considerations. The survey also dedicates a section to **Crop Monitoring Technologies**, discussing contributions of remote sensing, IoT, and AI-driven analytics to real-time agricultural management.

The **Conclusion** integrates the primary findings, highlighting the transformative potential of combining plant phenomics, LLMs, and AI in revolutionizing agricultural practices while addressing significant challenges such as the need for high-quality ground truth data in machine learning applications and the development of advanced phenotyping technologies. It outlines prospective research directions aimed at enhancing precision breeding and improving food security amidst climate change and growing global population demands [1, 29, 30]. This structured approach ensures readers gain a thorough understanding of the current landscape and future possibilities in leveraging advanced computational tools for precision agriculture.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Plant Phenomics and High-Throughput Phenotyping

Plant phenomics is a cornerstone of agricultural research, focusing on detailed trait analysis to enhance breeding and crop productivity. High-throughput phenotyping (HTP) technologies are crucial, enabling rapid, precise phenotypic assessments across large plant populations. These technologies collect accurate, multi-dimensional data, facilitating the analysis of complex traits under diverse environmental conditions. Automated, non-invasive HTP methods reduce human error and expedite phenotyping of extensive germplasm collections, thereby improving trait identification and genetic analysis, supporting both forward and reverse genetics to enhance crop breeding strategies [6, 9, 8, 31, 7]. Such advancements are vital for addressing global challenges like food security and climate change by developing resilient crop varieties.

HTP systems leverage advanced imaging and sensor technologies to gather comprehensive data on plant morphology, physiology, and growth dynamics, overcoming traditional phenotyping's labor-intensive limitations by enabling efficient management and analysis of large datasets. For instance, 3D scanning technologies offer detailed plant architecture reconstructions, providing insights into genotype-to-phenotype dynamics, while autonomous robotic platforms with high-resolution sensors enhance in-field data collection, enabling real-time plant development monitoring [32].

Integrating image-based phenotyping with deep learning automates specific plant feature detection and analysis, such as rice leaf tips, improving phenotypic assessment accuracy and efficiency [33]. Image augmentation techniques expand datasets for machine learning algorithms, bolstering phenotypic analysis robustness [34], while crowdsourcing training data generation is a promising strategy for developing effective machine learning models in plant phenomics [30].

Reliable phenotypic data collection methods are essential for measuring traits like morphology, chemistry, and metabolism across diverse environments. HTP technologies transform breeding by enhancing selection procedures and accelerating commercial cultivar development [31]. However, efficient crop trait characterization remains a challenge, crucial for advancing genetic improvements [1]. HTP integration in plant phenomics significantly advances agricultural research by enabling rapid, precise phenotypic data collection, enhancing superior crop variety breeding, addressing climate change and resource shortages, and contributing to sustainable agricultural practices to meet global food demands [9, 7, 1].

2.2 Large Language Models (LLMs) in Agriculture

Large Language Models (LLMs) are increasingly vital in agriculture, offering advanced data synthesis and decision-making capabilities. They excel at understanding and generating human-like text, crucial for analyzing diverse agricultural datasets and advancing precision agriculture. By encoding qualitative expert insights into structured features, LLMs enhance predictive analytics frameworks, facilitating informed agricultural decision-making [2].

Despite their potential, LLMs face challenges like hallucinations, outdated knowledge, and high operational costs, particularly relevant in agriculture [3]. Pruning methods requiring substantial computational resources can exacerbate these issues, leading to performance degradation [35]. Additionally, small and medium-sized agricultural enterprises often struggle with LLM adoption due to significant computational and data demands [36].

To mitigate these challenges, techniques like Retrieval-Augmented Generation (RAG) and Knowledge Retrieval enhance LLM reliability in agriculture by reducing hallucinations [37]. Frameworks such as AutoFlow automate workflow generation in natural language, enabling LLMs to interpret and execute agricultural tasks efficiently, minimizing human effort [38].

Generating high-quality synthetic data from LLMs is crucial, especially where real data is scarce or sensitive [39]. This optimizes LLM performance in data-limited agricultural contexts. Moreover, integrating LLMs in legal compliance and regulation within agriculture has significantly improved efficiency and accuracy over traditional methods [17].

LLMs hold transformative potential for agriculture, providing advanced tools for data analysis and decision support. However, addressing deployment challenges, including computational inefficiencies and ethical considerations, is critical for fully realizing their potential in agriculture [11].

2.3 Multimodal Large Models and Integration

Multimodal large models (MLLMs) are at the forefront of AI, integrating diverse data types like text, images, and sensory inputs for comprehensive analyses across domains, including agriculture. This capability is essential for enhancing decision-making in complex environments requiring nuanced understanding of multifaceted data [40]. The MM-Vet benchmark systematically evaluates core vision-language integration in MLLMs, emphasizing effective data synthesis.

Recent advancements, such as WorldGPT, introduce cognitive architectures enhancing MLLM predictive capabilities through memory offloading, knowledge retrieval, and context reflection, improving multimodal information utilization [41]. These innovations underscore MLLMs' potential to provide comprehensive insights by leveraging diverse data types, crucial in agriculture's complex decision-making contexts.

Niu et al. categorize MLLMs based on processing and integrating various modalities, highlighting the need for models bridging unstructured and structured data [42]. This categorization is vital for understanding MLLM applications in agricultural data, enabling precise decision-making.

The MA-LMM model introduces a long-term memory bank capturing historical video information, facilitating effective temporal agricultural data modeling [5]. This capability is essential for understanding crop development and environmental change temporal patterns, providing a robust framework for agricultural challenges.

High-quality multimodal datasets, such as those proposed by He et al., are crucial for training and evaluating MLLMs [43]. These datasets enable MLLMs to perform complex analyses with rich, varied inputs, enhancing their real-world agricultural applicability.

RSTeller distinguishes itself by integrating LLMs for generating rich captions at scale, significantly enhancing dataset semantic quality [44]. This approach emphasizes semantic richness in dataset creation, pivotal for training MLLMs to handle complex multimodal inputs effectively.

Integrating multimodal large models in agriculture holds transformative potential for data analysis and decision-making. By leveraging diverse data types, these models provide comprehensive, accurate insights, enhancing AI applications in complex, real-world scenarios. Ongoing benchmark and cognitive architecture development continues to drive MLLM evolution, ensuring alignment with human values and agriculture's specific needs [45].

In recent years, the field of plant phenomics has witnessed significant advancements, particularly in the realm of high-throughput phenotyping technologies. These innovations are essential for bridging the genotype-to-phenotype gap, which is crucial for improving crop resilience and yield. As illustrated in Figure 2, the hierarchical structure of key concepts in plant phenomics and phenotypic data analysis categorizes these advancements into several critical areas. The figure delineates advancements in high-throughput phenotyping technologies, plant stress phenotyping, and innovations in image-based phenotyping, while also addressing the processes of automated data collection and analysis.

Furthermore, it emphasizes the importance of managing large phenotypic datasets. Each category is meticulously broken down into technological advancements, applications, challenges, and future directions, thereby highlighting the interconnections among these elements and their contributions to agricultural research and crop improvement. This comprehensive overview not only enhances our understanding of the current landscape but also points to the pathways for future research in the field.

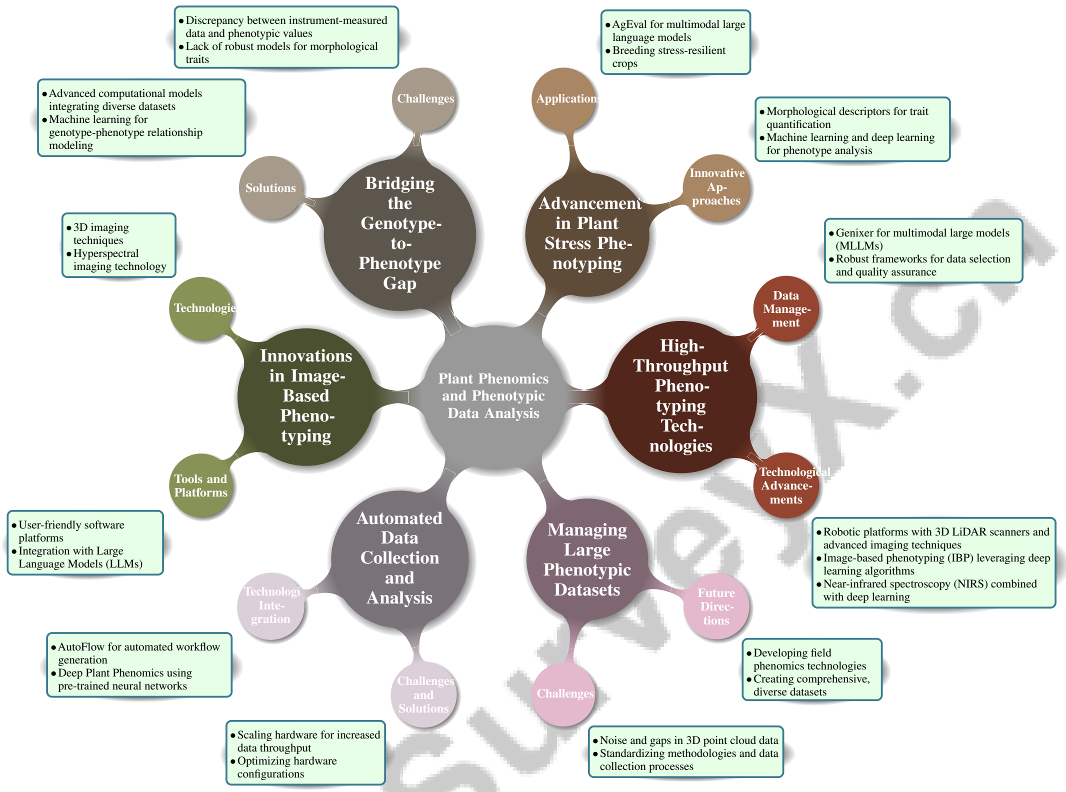


Figure 2: This figure illustrates the hierarchical structure of key concepts in plant phenomics and phenotypic data analysis, categorizing advancements in high-throughput phenotyping technologies, plant stress phenotyping, bridging the genotype-to-phenotype gap, innovations in image-based phenotyping, automated data collection and analysis, and managing large phenotypic datasets. Each category is further broken down into technological advancements, applications, challenges, and future directions, highlighting the interconnections and contributions to agricultural research and crop improvement.

3 Plant Phenomics and Phenotypic Data Analysis

3.1 High-Throughput Phenotyping Technologies

High-throughput phenotyping (HTP) technologies have revolutionized plant phenomics by facilitating rapid and precise trait evaluations across extensive plant populations. These technologies address the constraints of traditional phenotyping methods by enhancing the speed and accuracy of trait assessments through scalable solutions [1]. Robotic platforms with 3D LiDAR scanners and advanced imaging techniques capture detailed morphological data, enabling comprehensive analysis from micro-phenotyping to field-based assessments [1]. Image-based phenotyping (IBP), leveraging deep learning algorithms, distinguishes between drought-tolerant and susceptible genotypes, significantly advancing breeding programs by accelerating genetic gain and improving crop adaptation [9, 1, 7, 20, 30]. Near-infrared spectroscopy (NIRS) combined with deep learning exemplifies a non-destructive tool for assessing plant health and stress levels.

Data generation pipelines like Genixer empower multimodal large models (MLLMs) to autonomously create visual instruction tuning data, ensuring dataset quality and representativeness. Managing

AI-generated, for reference only.

substantial and heterogeneous multimodal data necessitates robust frameworks for data selection and quality assurance, as traditional large language models (LLMs) struggle with multimodal integration [25, 46, 47, 42]. Evaluation settings for HTP often include digitized plant morphology datasets, facilitating comprehensive comparisons with traditional morphometric methods. These techniques capture intricate traits through automated analysis and machine learning, processing vast data under varied conditions [6, 8].

HTP technologies are pivotal in plant phenomics, enabling analyses from molecular to whole-plant levels. Integrating high-throughput molecular analyses with phenotypic data enhances understanding of plant biology, facilitating the identification of superior genotypes under stress and driving innovative crop improvement strategies through efficient screening and data-driven breeding approaches [1, 9, 8, 7]. These technologies continue to propel agricultural research, contributing to sustainable and resilient agricultural systems.

3.2 Advancements in Plant Stress Phenotyping

Advancements in plant stress phenotyping focus on precision and scalability, crucial for developing stress-resilient crops. Traditional methods, reliant on expert evaluations, often suffer from subjectivity and labor intensity, limiting large-scale applications [48]. Innovative approaches enhance phenotypic analysis robustness and accuracy.

As illustrated in Figure 3, the figure highlights these advancements, emphasizing the role of morphological descriptors, machine learning, and deep learning in enhancing phenotypic analysis. It also addresses the limitations of traditional methods and the confinement of phenomics technologies to controlled environments, which restrict their real-world applicability [9]. Future directions, as depicted, focus on field phenomics and high-throughput data for improved genotype-phenotype associations.

Key innovations include morphological descriptors that improve trait quantification and modeling [49]. These descriptors provide detailed assessments of plant responses to stress, offering comprehensive morphology insights under varying conditions. Innovations address traditional method limitations by employing advanced descriptors and machine learning, particularly deep learning, enhancing phenotypic assessment robustness and scalability. This enables complex phenotype analysis in diverse field conditions, generating high-throughput data for improved genotype-phenotype association identification. Benchmarks like AgEval demonstrate multimodal large language models' potential in enhancing stress phenotyping task efficiency and accuracy, facilitating effective agricultural practices [6, 9, 8, 48]. These efforts are crucial for breeding crops resilient to environmental stresses from climate change.

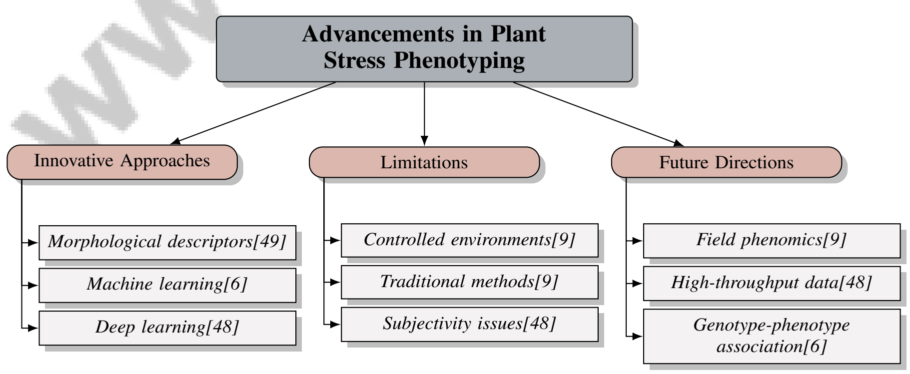


Figure 3: This figure illustrates the advancements in plant stress phenotyping, highlighting innovative approaches, existing limitations, and future directions. It emphasizes the role of morphological descriptors, machine learning, and deep learning in enhancing phenotypic analysis, while addressing the limitations of traditional methods and controlled environments. Future directions focus on field phenomics and high-throughput data for improved genotype-phenotype associations.

3.3 Bridging the Genotype-to-Phenotype Gap

Bridging the genotype-to-phenotype gap is critical for advancing plant biology and crop improvement. This gap poses challenges in integrating complex biological systems and vast data from high-throughput sequencing and phenotyping technologies to derive meaningful insights. Manual and image-based methods often inadequately measure complex traits across large datasets, limiting comprehensive analyses [6].

A primary challenge is the discrepancy between instrument-measured data and biologically meaningful phenotypic values, exacerbated by a lack of robust models for representing morphological traits [49]. Researchers are developing advanced computational models to integrate diverse datasets, including genomic, transcriptomic, and phenotypic data, to better understand the genetic architecture of complex traits.

Machine learning and deep learning techniques model intricate genotype-phenotype relationships, enabling precise identification of genetic markers linked to desirable traits, expediting breeding. Leveraging technologies for rapid, accurate phenotypic data collection allows researchers to develop resilient crop varieties, addressing climate change and food security challenges [31, 9, 1]. Integrating multi-omics data with phenotypic information provides a comprehensive plant physiology view, supporting novel trait association discovery and complex biological pathway elucidation.

A collaborative interdisciplinary approach is essential for effectively bridging the genotype-to-phenotype gap, focusing on sophisticated analytical frameworks managing intricate, voluminous data from modern phenomics technologies. These frameworks must address high-dimensional data challenges and facilitate diverse phenotypic measurement integration, crucial for understanding complex traits and enhancing genomic selection accuracy across varied contexts [6, 31, 7, 9]. By leveraging cutting-edge technologies and computational tools, researchers aim to transform raw data into biologically meaningful insights, driving innovations in plant breeding and agricultural sustainability.

3.4 Innovations in Image-Based Phenotyping

Innovations in image-based phenotyping have advanced plant phenomics by providing high-throughput, non-destructive trait analysis methods. These techniques leverage imaging technologies and sophisticated algorithms to capture detailed phenotypic data, facilitating precise plant morphology, physiology, and growth dynamics studies [50].

Key innovations include three-dimensional (3D) imaging techniques for comprehensive plant structure reconstruction. 3D models assess complex traits like architecture and biomass distribution, providing deeper genotype-phenotype relationship insights. Techniques like MLESAC and RANSAC have improved 3D correspondence algorithm precision and recall, with MLESAC generally outperforming RANSAC in speed [50].

Machine learning integration with image-based phenotyping enhances automatic plant feature detection and quantification. Deep learning models analyze extensive plant image datasets, facilitating precise complex trait classification and quantification, surpassing traditional image processing methods. High-throughput systems using deep learning explore intricate phenotypic features, enhancing genotype-phenotype associations and advancing agricultural practices [6, 29, 30]. These advancements enable rapid desirable characteristic screening, accelerating breeding and supporting stress-resilient crop variety development.

Hyperspectral imaging technology, capturing a comprehensive spectrum of wavelengths, enhances physiological parameter monitoring quickly and non-destructively, facilitating plant trait analysis under varied conditions [8, 51, 29, 7, 30]. This technique detects subtle physiological changes not visible to the naked eye, offering valuable plant-environment interaction insights and aiding early stress factor identification.

User-friendly software platforms for image-based phenotyping have contributed to widespread technique adoption in agricultural research. These platforms provide advanced tools for comprehensive data management, in-depth analysis, and dynamic visualization, optimizing the phenotyping process and fostering effective, data-driven decision-making. By leveraging Large Language Models (LLMs), they automate critical research stages, enhancing efficiency and accuracy in scientific review and predictive analytics [16, 12, 19].

Innovations in image-based phenotyping transform plant trait study, offering powerful tools for enhancing plant biology understanding and crop performance improvement. By combining imaging technologies with advanced data analysis techniques, researchers perform detailed and accurate phenotypic assessments on a large scale. This integration enhances data collection precision and facilitates high-quality ground truth data generation through methods like crowdsourcing, crucial for addressing climate change and population growth challenges in agriculture, contributing to sustainable farming practices and food security [6, 7, 9, 30].

3.5 Automated Data Collection and Analysis

Automating data collection and analysis in plant phenomics represents a transformative advancement, facilitating efficient and precise phenotypic trait assessment across diverse plant populations. This progress is largely attributed to integrating cutting-edge technologies and computational tools that streamline large-scale phenotypic dataset management. AutoFlow exemplifies this advancement by generating and optimizing workflows automatically, allowing Large Language Models (LLMs) to execute complex tasks efficiently, crucial for managing extensive phenotypic datasets [38].

High-throughput phenotyping technologies have significantly improved phenotypic data collection efficiency and accuracy through automation and imaging technology advancements [1]. These technologies enable rapid acquisition of detailed plant trait data, essential for enhancing genomic selection prediction accuracy in breeding programs [31]. Automated systems like Deep Plant Phenomics leverage pre-trained neural networks for complex analyses with minimal manual intervention, reducing data processing time and labor [6].

Innovative methods like image augmentation enhance data collection and analysis by expanding training dataset diversity. By synthesizing compound scenes from existing image-mask pairs, these methods improve phenotypic model robustness and generalizability [34]. Additionally, extracting local features from 3D point clouds facilitates precise plant morphology and development characterization, underscoring automation's role in phenotypic analysis [51].

Despite advancements, challenges remain in scaling hardware to accommodate increasing data throughput. Experiments show diminishing returns in throughput and hardware utilization as accelerators increase, highlighting the need for optimized hardware configurations in automated phenomics systems [52]. These findings emphasize developing scalable and efficient hardware solutions to support growing phenotypic data analysis demands.

Automating data collection and analysis in plant phenomics has significantly improved phenotypic study reproducibility and scalability. By harnessing cutting-edge technologies and innovative methodologies, researchers perform swift, non-destructive measurements and efficiently analyze extensive datasets with minimal preprocessing. This advancement boosts trait-based research efficiency and accuracy, integrates expert domain knowledge into quantifiable features, enhances predictive analytics, and supports robust statistical frameworks for high-throughput phenotyping. These developments facilitate comprehensive complex trait assessments across diverse populations, advancing plant genetics understanding and improving agricultural research decision-making processes [30, 31, 7, 16].

3.6 Managing Large Phenotypic Datasets

Managing large phenotypic datasets presents significant challenges in plant phenomics due to large-scale experiment complexity and diverse data source integration. These experiments' intricacy necessitates numerous interlinked tools, efficiently coordinated for reproducibility and effective diverse dataset handling [53]. Phenotyping platforms' operational costs further compound these challenges, requiring substantial resources for data collection, storage, and analysis [1].

A main issue in managing large datasets is noise and gaps in 3D point cloud data, complicating detection and description processes. Existing methods often fall short, necessitating robust algorithms capable of handling such imperfections [51]. Additionally, standardizing methodologies and data collection processes is critical, as inconsistencies hinder data integration and analysis across different platforms [8].

Future research should prioritize developing field phenomics technologies capable of generating realistic, multi-dimensional phenotypic data. These solutions should be user-friendly and cost-effective, enabling broader accessibility and application in diverse agricultural contexts [9]. The

LHRS-Align dataset, encompassing approximately 1.15 million image-caption pairs, exemplifies the rich and diverse datasets necessary for effectively training and evaluating multimodal large models (MLLMs) in remote sensing, highlighting comprehensive datasets' importance in advancing phenotypic research [54].

Addressing large phenotypic dataset management challenges requires a multifaceted approach encompassing advanced data processing techniques, methodology standardization, and comprehensive, diverse dataset creation. Effectively addressing these challenges can significantly improve phenotypic analysis efficiency and precision, crucial for advancing plant phenomics employing high-throughput technologies to gather comprehensive phenotypic data across diverse environmental conditions. Such advancements facilitate complex trait identification suitable for selection and play a vital role in driving agricultural innovation and improving crop yield potential in response to growing climate change demands and increasing global population [6, 9, 8, 7, 20].

4 Large Language Models and Multimodal Models in Agriculture

Category	Feature	Method
Applications of LLMs in Agriculture	Process Automation	AF[38], ATLS[32], LLM-CCM[17]
Capabilities of Multimodal Models	Modality Interaction	AMMG[55], MOWL2[56]
Current Models and Frameworks	Model Behavior Control	PKE[57]
Influence of Large Language Models on Decision-Making	Model Optimization Techniques Transparency and Interpretability	LS[35], P-LM[58] LLM-AI[59]
Multimodal Model Applications in Agriculture	Data Augmentation	MCMLLM[60], N/A[61], MOWL[62]

Table 1: This table provides a comprehensive overview of various methodologies applied within the domains of large language models (LLMs) and multimodal models in agriculture. It categorizes these methodologies into distinct areas such as process automation, modality interaction, model behavior control, model optimization techniques, and data augmentation. The table highlights the specific features and methods employed in each category, showcasing the diverse applications and capabilities of these models in enhancing agricultural practices.

The transformative impact of Large Language Models (LLMs) in agriculture is demonstrated through their diverse applications, enhancing data-driven decision-making and optimizing agricultural processes. Table 1 presents a detailed categorization of methods and features associated with the applications and capabilities of large language models and multimodal models in agriculture, illustrating their impact on process automation, modality interaction, and model optimization. Additionally, Table 3 offers a comprehensive overview of the methods and features associated with the applications of large language models and multimodal models in agriculture, demonstrating their transformative impact on process automation, modality interaction, and model optimization. This section examines LLM applications, focusing on compliance verification, workflow optimization, and ethical considerations, highlighting their significant influence on the agricultural landscape.

4.1 Applications of LLMs in Agriculture

LLMs are increasingly essential in agriculture, significantly improving data analysis and decision-making. Their capacity to process and integrate complex datasets is vital for advancing precision agriculture. Recent advancements in natural language understanding and generation have enabled LLMs to perform complex tasks with minimal fine-tuning, enhancing their applicability in agriculture [4]. A prominent application is automating compliance checking for food safety regulations. By classifying regulatory texts, LLMs enhance the efficiency and accuracy of compliance verification, ensuring adherence to safety standards in agricultural production [17]. This capability is critical for maintaining food safety across diverse agricultural systems. LLMs also optimize agricultural workflows, as demonstrated by experiments on the OpenAGI benchmark dataset using both closed-source (GPT-4) and open-source (Mixtral-8x7B) models, which automate tasks and reduce manual effort in data management and analysis [38]. The semantic router framework has outperformed traditional prompting methods in managing linguistic variability, enhancing the reliability and precision of LLM outputs in global agricultural contexts [37]. Addressing ethical concerns, such as user privacy and accountability, LLMs facilitate robust ethical frameworks, establishing trust in AI-driven agricultural applications [14]. Their ongoing advancements in various domains, including healthcare and finance, further underscore their transformative potential in agriculture [11]. The diverse applications of LLMs in agriculture are expanding, driven by their ability to automate and enhance data-driven decision-making processes.

As illustrated in Figure 5, this figure illustrates the key applications of Large Language Models (LLMs) in agriculture, highlighting their roles in automating compliance checking, optimizing workflows, and establishing ethical frameworks. These applications demonstrate the transformative potential of LLMs in enhancing precision, productivity, and decision-making in agricultural practices. As LLMs evolve, their role in revolutionizing agricultural practices is expected to grow, offering new opportunities for enhancing productivity and sustainability [28].

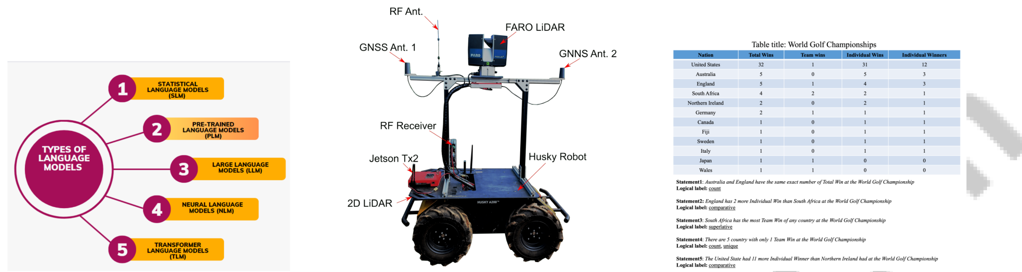


Table title: World Golf Championships

Nation	Total Wins	Team wins	Individual Wins	Individual Winners
United States	32	1	31	12
Australia	5	0	5	3
England	5	1	4	3
South Africa	4	2	2	1
Northern Ireland	2	0	2	1
Germany	2	1	1	1
Canada	1	0	1	1
Fiji	1	0	1	1
Sweden	1	0	1	1
Italy	1	0	1	1
Japan	1	1	0	0
Wales	1	1	0	0

Statement1: *Australia and England have the same exact number of Total Win at the World Golf Championship*
Logical label: count

Statement2: *England has 2 more Individual Win than South Africa at the World Golf Championship*
Logical label: comparative

Statement3: *South Africa has the most Team Win of any country at the World Golf Championship*
Logical label: superlative

Statement4: *There are 5 country with only 1 Team Win at the World Golf Championship*
Logical label: count, unique

Statement5: *The United State had 11 more Individual Winner than Northern Ireland had at the World Golf Championship*
Logical label: comparative

(a) Types of Language Models[21]

(b) A Husky Robot with Various Sensors and Equipment[32]

(c) World Golf Championships[12]

Figure 4: Examples of Applications of LLMs in Agriculture

Collectively, these examples underscore the transformative potential of LLMs and multimodal models in enhancing precision, productivity, and decision-making in agriculture [21, 32, 12].

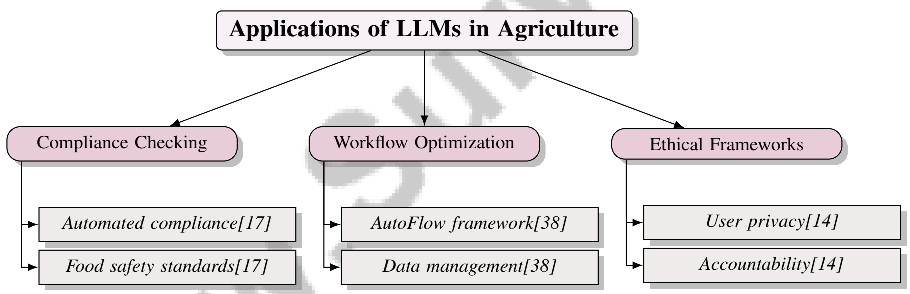


Figure 5: This figure illustrates the key applications of Large Language Models (LLMs) in agriculture, highlighting their roles in automating compliance checking, optimizing workflows, and establishing ethical frameworks. These applications demonstrate the transformative potential of LLMs in enhancing precision, productivity, and decision-making in agricultural practices.

4.2 Capabilities of Multimodal Models

Multimodal models have emerged as powerful tools for processing diverse agricultural data, significantly advancing the integration and analysis of information from various sources. These models excel in tasks requiring the synthesis of different data modalities, such as text, images, and sensory inputs, providing comprehensive insights into complex agricultural systems. The MM-Vet framework exemplifies this capability by offering a thorough evaluation of integrated multimodal capabilities, yielding deeper insights than traditional benchmarks [40]. Integrating multimodal data enhances diagnostic accuracy and stakeholder engagement through interactive applications [42]. This is particularly relevant in agriculture, where fusing data from multiple sources can lead to more accurate predictions and informed decision-making. The survey by Qian et al. categorizes the roles of LLMs in Cross-Modal Retrieval (CMR) into Multimodal Fusion Engine, Textual Processor, Cognitive Controller, and Knowledge Enhancer, highlighting their multifaceted capabilities in processing diverse data types [24]. Recent advancements, such as mPLUG-Owl, demonstrate the ability of multimodal models to generalize across tasks and facilitate modality collaboration, enhancing performance without interference drawbacks [56]. This is achieved through a two-stage training process that aligns image and text data, improving the model's ability to understand and generate multimodal outputs [62]. Such innovations underscore the potential of multimodal models to transform agricultural data analysis by providing nuanced and contextually relevant insights. The Any-to-Many Modalities Generation (AMMG) framework, exemplified by Spider, allows for generating arbitrary combinations of modalities in a single response, enabling a flexible approach to data processing [55]. This versatility is crucial for addressing the complex data requirements in agriculture, where integrating multiple data streams can improve monitoring and management of agricultural systems. Challenges remain in fine-grained recognition and counting tasks, as recent evaluations of multimodal models indicate [63]. Continued research and development are necessary to enhance the precision and reliability of these models in processing detailed agricultural data. The Precision Knowledge Editing (PKE) technique offers a promising approach by tracking neuron weight changes and activation pathways, thereby improving the identification and modification of parameters impacting model performance [57]. The capabilities of multimodal models in processing diverse agricultural data are vast and evolving. By employing cutting-edge integration and synthesis techniques, these models can significantly transform agricultural practices, enhancing productivity and sustainability through high-quality ground truth data generated by crowdsourcing and advanced phenotyping technologies. This integration facilitates precise identification of phenotypic traits, effective monitoring of crop health, and informed decision-making, ultimately addressing critical challenges in food security, climate change, and resource management [1, 63, 30].

4.3 Integration of Diverse Data Types

The integration of diverse data types is a critical capability of multimodal large models (MLLMs), enabling comprehensive agricultural analysis through synthesizing information from various sources. This integration is essential for improving the interpretability and effectiveness of models in complex agricultural scenarios. The MLLM architecture, explored by Zhang et al., emphasizes structured approaches for integrating various modalities, vital for processing and analyzing diverse agricultural data [64]. A primary challenge in integrating diverse data types is the limitation of LLMs in understanding complex reasoning and effectively synthesizing multimodal data. Innovative methods, such as the Tree-of-Thoughts (ToT) prompting technique, allow LLMs to explore multiple reasoning paths and select optimal outputs, enhancing their ability to integrate and analyze diverse data types in agricultural contexts [27]. The modularized network design utilized in mPLUG, with a language decoder serving as a universal interface, exemplifies the effectiveness of modularized learning in managing multimodal signals. This approach facilitates targeted improvements in multimodal understanding and generation, enabling seamless integration of diverse data types for agricultural analysis [40]. Additionally, the LLM2LLM method focuses on augmenting only misclassified examples, improving the model's performance on challenging tasks. This targeted augmentation is crucial for effectively integrating diverse data types, ensuring robust and reliable agricultural analyses [12]. The QUALEVAL method introduces a flexible linear programming solver to assign attributes to input instances, enabling detailed and interpretable analysis of model behavior relevant to agricultural data [41]. This approach enhances the model's ability to process and integrate diverse data types, providing nuanced insights into agricultural systems. Furthermore, Scherbakov et al. categorize existing research based on automation stages in systematic reviews where LLMs are applied, such as searching, data extraction, and evidence synthesis. This framework highlights the potential of LLMs to automate and enhance the integration of diverse data types in agricultural research [43]. The integration of diverse data types in MLLMs offers significant potential for enhancing agricultural analysis by providing comprehensive insights into complex agricultural systems. By leveraging advanced integration techniques and robust datasets, these models can facilitate more accurate and informed decision-making, ultimately contributing to the advancement of precision agriculture [18].

4.4 Current Models and Frameworks

The development of multimodal models has evolved through four distinct stages: Single modality (1980-2000), Modality conversion (2000-2010), Modality fusion (2010-2020), and Large-scale multimodal (2020-present) [46]. This progression highlights the increasing complexity and capability of models to integrate diverse data types, crucial for agricultural applications. The current era of large-scale multimodal models is characterized by their ability to synthesize information from various sources, enhancing decision-making processes in agriculture. Notable advancements include MAP-Neo, an open-sourced bilingual LLM that provides detailed training data, pipeline, and evaluation

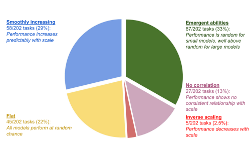
Benchmark	Size	Domain	Task Format	Metric
LMM-ViT-Cyber[65]	12,393	Cybersecurity	Trigger Detection	Accuracy, F1-score
GPT-4V[63]	100,000	Geography	Visual Question Answering	Accuracy, F1-score
AgEval[48]	1,200	Plant Stress Phenotyping	Identification	F1-score, NMAE
ProcessTBench[66]	532	Process Mining	Plan Generation	Alignment Fitness, Replay Fitness
ACRT[67]	800	Cultural Bias Evaluation	Bias Detection	Attack Success Rate, Bias Classification Accuracy
Crowdsource-Corn-Tassels[30]	80	Plant Phenomics	Image Segmentation	F1-score
LinguisticLens[68]	500	Dialogue Systems	Text Generation	Diversity Score, Syntactic Similarity
LLM-lncRNA[69]	53,066	Genomics	Sequence Classification	MCC, Accuracy

Table 2: This table provides a comprehensive overview of various benchmarks used in evaluating large-scale multimodal models. It details the benchmark name, size, domain, task format, and evaluation metrics, offering insights into the diversity and scope of current evaluation frameworks. These benchmarks are critical for assessing model performance across different domains and applications.

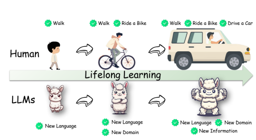
metrics. This model matches the performance of proprietary models while setting a new standard for transparency, essential for building trust in AI-driven agricultural applications [64]. Its transparency and accessibility make it a valuable tool for agricultural researchers and practitioners seeking to leverage AI technologies for data analysis and decision support. The integration of VecDBs with LLMs enhances data retrieval capabilities while reducing operational costs in agricultural applications [70]. This integration allows for efficient data management and retrieval, critical for handling the vast amounts of data generated in modern agricultural systems. Furthermore, the Precision Knowledge Editing (PKE) technique introduces advanced mathematical formulations and a structured editing process that provides finer granularity in managing toxic content compared to previous methods like DINM [57]. This level of granularity is particularly important in agricultural applications, where accurate and reliable data is paramount for effective decision-making. WorldGPT exemplifies multimodal model applications in agriculture by evaluating models on distinct scenarios to assess their ability to predict state transitions [41]. This approach underscores the importance of robust evaluation frameworks in ensuring that models can effectively handle the dynamic and complex nature of agricultural environments.

As depicted in Figure 7, this figure illustrates the hierarchical structure of current models and frameworks in agricultural applications, highlighting the stages of multimodal model development, key advancements, and their applications in agriculture. The current models and frameworks in agricultural applications reflect significant advancements in integrating diverse data types and enhancing model transparency and efficiency. The integration of advanced AI technologies, particularly LLMs, is revolutionizing agricultural practices by transforming expert insights into quantifiable data, enhancing predictive analytics and decision-making. These innovations facilitate adopting more effective and sustainable farming methods through data-driven insights from diverse sources, including satellite imagery and ground-level observations. Consequently, the agricultural sector can leverage these sophisticated tools to improve risk assessment, optimize resource management, and address environmental challenges, paving the way for a more resilient and sustainable agricultural future [18, 63, 16].

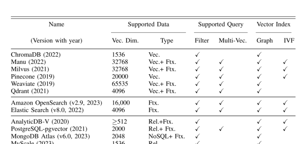
Table 2 presents a detailed summary of representative benchmarks employed in the evaluation of large-scale multimodal models, highlighting their relevance across diverse domains and tasks.



(a) Performance Trends in Large Model Training[23]



(b) Human and LLMs in Lifelong Learning: A Comparative Analysis[71]



(c) Comparison of Different Database Systems and Their Features[70]

Figure 6: Examples of Current Models and Frameworks

As illustrated in Figure 7, the integration of LLMs and multimodal models in agriculture is a burgeoning research area, highlighting the transformative potential of AI in this vital sector. Current models and frameworks being explored are illustrated through various examples that underscore the diversity and depth of these technological advancements. One example is the performance trends in large model training, depicted in a pie chart categorizing tasks based on performance trends, providing insights into how scaling impacts model performance across different tasks. Another example focuses on lifelong learning, drawing parallels between human learning processes and those of LLMs. This comparative analysis is visualized with imagery of a human progressing from walking to driving, alongside alpacas symbolizing LLMs mastering new languages and domains. Additionally, a tabular comparison of different database systems details their features, such as supported data types and query capabilities, aiding in understanding the diverse functionalities offered by various databases, crucial for managing and utilizing agricultural data effectively. Collectively, these examples reflect the current state of models and frameworks in agriculture, underscoring the potential of LLMs and multimodal models to enhance efficiency, decision-making, and innovation in the agricultural sector [23, 71, 70].

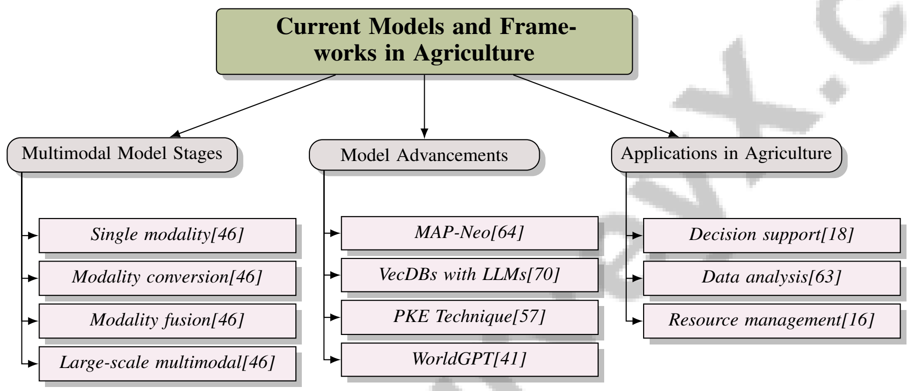


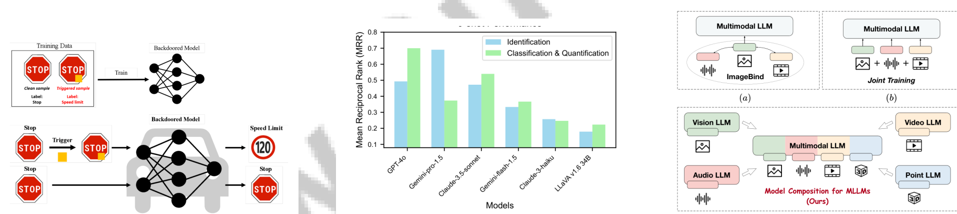
Figure 7: This figure illustrates the hierarchical structure of current models and frameworks in agricultural applications, highlighting the stages of multimodal model development, key advancements, and their applications in agriculture.

4.5 Influence of Large Language Models on Decision-Making

LLMs are increasingly pivotal in enhancing decision-making processes within agriculture through their advanced data analysis and integration capabilities. They facilitate synthesizing complex datasets essential for precision agriculture, enabling informed strategic planning and operational efficiency. Techniques like structured pruning and knowledge recovery, such as LoRAShear, optimize LLMs by reducing model size while maintaining performance, crucial for resource-limited agricultural settings [35]. The multidimensional capabilities of LLMs streamline benchmark development and improve predictions about model behavior, enhancing the reliability of decision-making frameworks [72]. However, challenges such as ethical considerations, model biases, and interpretability issues remain significant, necessitating careful consideration to ensure LLMs contribute positively to agricultural decision-making [11]. Exploring moral reasoning capabilities, as suggested by Tlaie et al., is crucial for understanding the ethical dimensions of LLM deployment in agriculture [45]. LLMs articulate complex relationships and trade-offs in a human-understandable manner, enhancing decision-making transparency, as evidenced by LLM-Assisted Inference effectiveness [59]. This transparency is vital for addressing the dynamic and multifaceted nature of agricultural systems, where adaptive and flexible decision-making is required. The scalability of LLMs further enhances their capabilities, allowing improved performance on complex tasks such as predicting plant responses to diverse environmental conditions [73]. Moreover, LLMs generate multiple plan variants with varying degrees of alignment to the ground truth, indicating reliability and diversity in decision-making frameworks. This diversity is essential for addressing complex challenges in agricultural systems [58]. The PORTLLM model exemplifies this potential by maintaining or enhancing performance on downstream tasks without repeated fine-tuning, demonstrating the efficiency of LLMs in agricultural decision-making [58].

4.6 Multimodal Model Applications in Agriculture

Multimodal models have become pivotal in agriculture, providing innovative solutions by integrating diverse data types to enhance decision-making processes and operational efficiencies. These models leverage the synthesis of text, images, and sensory data, facilitating comprehensive analyses that are crucial for addressing complex agricultural challenges [61]. The ability of multimodal large models (MLLMs) to autonomously generate synthetic datasets, as demonstrated by Genixer, underscores their potential as powerful data generators, enhancing performance across various agricultural benchmarks without external data inputs [61]. In precision farming, multimodal models enhance monitoring and management of crop health by integrating diverse data sources such as satellite imagery, aerial photographs, ground-level images, and real-time sensor data. This integration improves capabilities in tasks like crop type identification, disease and pest recognition, and overall land cover classification, facilitating informed agricultural decision-making and contributing to food security amid climate change and population growth challenges [54, 63, 30]. It allows for real-time analysis of environmental conditions and crop status, leading to informed decisions on irrigation, fertilization, and pest control. The use of multimodal models in this context not only improves yield predictions but also optimizes resource use, contributing to sustainable agricultural practices. Additionally, multimodal models enhance document comprehension within agricultural research and policy development. Future research should focus on improving these models' performance in understanding complex agricultural documents, enabling better interpretation of regulatory texts and scientific literature [62]. This capability is essential for ensuring compliance with agricultural policies and disseminating critical research findings to stakeholders. The application of multimodal models extends to developing intelligent systems for automated crop disease detection. By combining visual imagery with environmental and historical data, these models can identify disease symptoms early, facilitating timely interventions and reducing crop losses. Integrating audio data for monitoring animal health and behavior in livestock farming represents a promising application of multimodal models, enhancing our understanding of animal welfare and productivity by combining auditory signals with visual and textual data, providing a comprehensive analysis of livestock conditions [27, 46, 63, 42].



(a) Backdoored Model: A Technique for Improving Traffic Sign Recognition Accuracy[65]

(b) Comparison of Mean Reciprocal Rank (MRR) for Identification and Classification Quantification Models[48]

(c) Model Composition for Multimodal Language Models (MLLMs)[60]

Figure 8: Examples of Multimodal Model Applications in Agriculture

As shown in Figure 8, the integration of LLMs and multimodal models is revolutionizing data utilization and interpretation in modern agriculture. The application of these advanced models is illustrated through three distinct examples, each highlighting a unique aspect of this technological evolution. The first example, "Backdoored Model: A Technique for Improving Traffic Sign Recognition Accuracy," demonstrates how neural networks can be manipulated to enhance recognition accuracy by using a mix of clean and triggered samples, showcasing the potential for similar techniques to be adapted for agricultural purposes such as crop disease detection. The second example presents a comparative analysis of model performance, emphasizing the importance of selecting the right model for specific agricultural tasks, whether it be identification or classification of plant species. Lastly, "Model Composition for Multimodal Language Models (MLLMs)" explores innovative approaches to training MLLMs, such as ImageBind and joint training, pivotal in integrating diverse data types like imagery and textual information to enhance decision-making processes in agriculture. These examples collectively underscore the transformative impact of LLMs and multimodal models in advancing agricultural technologies and methodologies [65, 48, 60].

Feature	Applications of LLMs in Agriculture	Capabilities of Multimodal Models	Integration of Diverse Data Types
Application Area	Compliance Verification	Data Synthesis	Agricultural Analysis
Data Integration	Minimal Fine-tuning	Multimodal Fusion	Tree-of-Thoughts Technique
Model Advancement	Semantic Router Framework	Mplug-Owl Generalization	Qualeval Method

Table 3: This table provides a comparative analysis of various methods and features associated with the applications and capabilities of large language models (LLMs) and multimodal models in agriculture. It highlights key areas such as compliance verification, data synthesis, and agricultural analysis, as well as the integration techniques and model advancements employed to enhance these applications.

5 Precision Agriculture Decision-Making

Effective decision-making in precision agriculture is crucial for optimizing productivity and sustainability. This section explores foundational methodologies like structured workflows and evidence scoring, which enhance agricultural practices by integrating diverse datasets and utilizing advanced computational tools. These methodologies enable more informed agricultural strategies, as detailed in the following subsection.

5.1 Structured Workflows and Evidence Scoring

Structured workflows and evidence scoring are essential for precision agriculture, offering a systematic approach to improving decision-making. By facilitating the integration and analysis of diverse datasets, these methodologies lead to more accurate agricultural practices. The integration of Large Language Models (LLMs) and Multimodal Large Models (MLLMs) has advanced structured workflows by automating complex data processing tasks, reducing manual effort in agricultural data management [38].

LLMs automate systematic review stages, including publication searches, data extraction, and drafting, which are vital for evidence-based agricultural decision-making [19]. This automation enhances evidence synthesis efficiency and accuracy, providing a robust foundation for responsive agricultural strategies.

Evidence scoring assesses and quantifies data reliability and relevance, ensuring decision-making is based on high-quality evidence. Advanced computational tools like LLMs improve the evaluation of large data volumes, facilitating precise agricultural analyses [28]. Frameworks such as AutoFlow, which automates workflow generation in natural language, exemplify how LLMs streamline structured workflows in precision agriculture [38]. This automation enhances data processing efficiency and scalability, enabling the management of complex datasets.

Structured workflows and evidence scoring are foundational to precision agriculture, providing tools for integrating diverse data sources and ensuring evidence-based decision-making. Leveraging LLMs and MLLMs, these methodologies offer substantial opportunities for enhancing agricultural productivity and sustainability. They facilitate regulatory compliance, improve data interpretation, and integrate expert insights into predictive analytics, addressing modern agricultural demands and environmental concerns [74, 17, 16, 12, 42].

5.2 Optimizing Resource Use through Data-Driven Decisions

Optimizing resource use through data-driven decisions is central to precision agriculture, utilizing advanced computational tools to enhance efficiency and sustainability. LLMs and MLLMs contribute significantly by automating workflow creation and synthesizing complex datasets, improving task execution and resource allocation [38]. AutoFlow exemplifies this by enabling seamless workflow generation, optimizing resource use through enhanced task execution and data management.

As illustrated in Figure 9, the hierarchical structure for optimizing resource use highlights key areas such as automating workflows, enhancing breeding, and improving decision reliability in precision agriculture. Adaptive prompt generation capabilities of models like LDM2 further enhance decision-making by leveraging relevant past experiences to inform new situations [75]. This adaptability is crucial for optimizing resource use in dynamic agricultural environments. By utilizing historical data and contextual information, LDM2 supports effective decision-making, contributing to efficient resource utilization.

Integrating High-Throughput Phenotyping (HTP) data into genomic selection models enhances prediction accuracy and streamlines the breeding process, optimizing resource use in agriculture [31]. This approach allows for precise selection of desirable traits, reducing time and resources in breeding programs.

Autonomous robotic platforms, such as ground mobile robots, reduce labor requirements and increase data collection efficiency, optimizing resource use in plant trait assessment [32]. These technologies enable accurate data collection, supporting informed decision-making and resource allocation.

Metrics measuring the correctness of responses and the usefulness of information provided by LLMs enhance data-driven decision reliability [76]. This reliability is essential for ensuring resource optimization strategies are based on accurate information.

Data-driven decisions optimize resource use by leveraging advanced computational tools and methodologies. By integrating LLMs and MLLMs, automating workflows, and utilizing innovative data augmentation techniques, agricultural systems can improve operational efficiency and sustainability. This approach enhances predictive analytics precision by translating expert knowledge into actionable features, addressing data scarcity challenges and leading to resilient agricultural practices. These advancements contribute to a robust framework capable of responding to modern food production complexities and regulatory compliance [74, 17, 16, 18, 12].

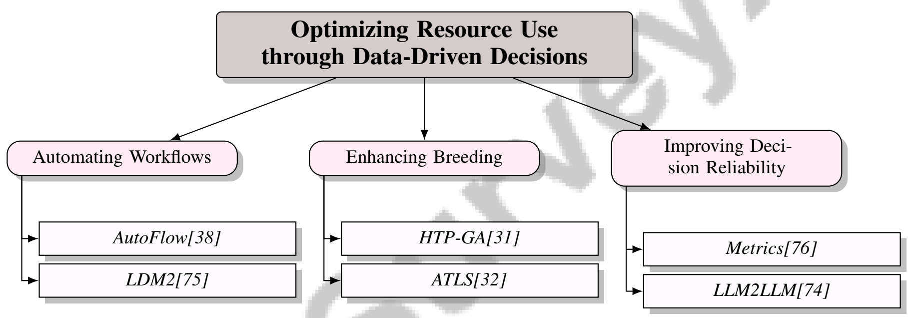


Figure 9: This figure illustrates the hierarchical structure for optimizing resource use through data-driven decisions, highlighting key areas such as automating workflows, enhancing breeding, and improving decision reliability in precision agriculture.

5.3 Technological Advancements and Decision-Making

Technological advancements in AI, particularly in LLMs and MLLMs, have transformed decision-making in agriculture. These models enhance the integration and analysis of diverse data types, providing comprehensive insights into complex agricultural systems. The LLM-Assisted Inference framework improves understanding of key decision variables in optimization scenarios, facilitating informed decision-making [59].

Multimodal data integration, as demonstrated by systems like MaintAGT, enhances diagnostic capabilities, improving fault diagnosis accuracy compared to traditional methods [77]. This capability is crucial for precision agriculture, where accurate diagnostics lead to effective resource management. The MA-LMM model's ability to reference historical video content while processing new frames enhances decision-making by improving data analysis capabilities, allowing better temporal understanding of agricultural processes [5].

Challenges remain in managing high computational costs and handling diverse modalities [78]. Addressing these challenges is essential for fully realizing AI technologies' potential in agriculture. The mPLUG-Owl2 model addresses some issues by preserving modality-specific characteristics while enabling collaboration, enhancing understanding and performance across diverse tasks [56].

The QUALEVAL model contributes to decision-making by providing a holistic view of model behavior, significantly accelerating the model improvement lifecycle [79]. This acceleration is vital for adapting to rapidly changing agricultural conditions. Additionally, the comparative effectiveness of LLMs and Vision Transformers (ViTs) in cybersecurity tasks provides valuable insights into fine-tuned models' strengths, which can enhance agricultural decision-making [65].

Technological advancements in AI, particularly LLMs like GPT-4V, are transforming agricultural decision-making. These models offer innovative tools for integrating and analyzing complex datasets, enabling tasks like crop type identification, disease recognition, and agricultural object counting. Consequently, they enhance agricultural practices' efficiency and provide insights into environmental and urban planning applications, showcasing potential for interdisciplinary advancements [80, 63]. By addressing existing challenges and leveraging advanced computational models' strengths, the agricultural sector can enhance productivity and sustainability, contributing to more informed decision-making.

6 Artificial Intelligence in Agriculture

The integration of artificial intelligence (AI) is revolutionizing agriculture by enhancing productivity and addressing critical challenges. This section delves into the role of advanced technologies, notably Large Language Models (LLMs) and Multimodal Large Models (MLLMs), in transforming agricultural practices. By exploring their diverse applications, we can understand AI's transformative potential and implications for sustainable agriculture. The following subsection will offer a detailed analysis of AI technologies' specific contributions to this field.

6.1 Broader Role of AI in Agriculture

AI is pivotal in agriculture, offering innovative solutions that enhance productivity, sustainability, and decision-making. Technologies like LLMs and MLLMs address complex agricultural challenges through data synthesis, predictive analytics, and workflow optimization. AutoFlow, for instance, automates workflow generation, boosting efficiency and reducing reliance on human expertise, which is crucial for managing complex agricultural data and supporting informed decision-making [38].

The MA-LMM illustrates AI's capabilities by enabling video analysis for long-term monitoring of crop growth and environmental conditions, thereby supporting sustainable practices [5]. Additionally, the MM-Vet benchmark evaluates LLMs' vision-language integration, highlighting their potential to enhance agricultural monitoring by integrating diverse data types [40]. Insights from Burnell et al. on LLM capabilities contribute to more efficient benchmarks, fostering innovation in AI-driven agricultural applications [72].

AI also enhances breeding strategies by integrating genomic and phenotypic data, facilitating the development of resilient crop varieties through robust quantification methods [31]. Furthermore, models like LoRAShear, which optimize LLMs while maintaining performance, underscore AI's potential for efficient resource use and data management in agriculture [35].

Ethical considerations are paramount in AI's agricultural role, particularly concerning biases in LLM training data. Addressing these biases is critical to ensuring that AI technologies positively impact agricultural practices [14]. The exploration of moral reasoning capabilities, as suggested by Tlaie et al., is vital for understanding the ethical dimensions of AI deployment in agriculture [45].

AI's transformative potential in agriculture is characterized by its diverse applications, addressing challenges related to data integration, model transparency, and ethical considerations. Research highlights LLMs' strengths in engaging with complex ethical dilemmas, further supporting their role in advancing agricultural practices [3].

6.2 Ethical and Practical Considerations

The integration of AI in agriculture, particularly through LLMs and MLLMs, presents ethical and practical challenges requiring careful consideration. A significant ethical concern is the potential bias in LLM training data, which can result in misleading or harmful outputs. Ensuring transparency in AI systems is essential for identifying and mitigating these biases to prevent negative impacts on agricultural practices [22].

The environmental impact of training and deploying LLMs is another critical ethical consideration, given the substantial computational resources required, which can increase carbon emissions. This

AI-generated, for reference only.

underscores the need for sustainable practices and efficient hardware configurations to optimize training and address communication bottlenecks [52]. Furthermore, the high resource demands of LLMs may limit their accessibility in regions with limited technological infrastructure, highlighting the need for scalable and efficient AI solutions [21].

Practical challenges include the necessity for high-quality data to train AI models effectively, which may not always be available in agricultural contexts. The effectiveness of pruning techniques like LoRAShear relies on the quality of dependency graph analysis, indicating a need for further optimization across various neural network architectures [35].

Moreover, deploying LLMs raises concerns about AI system transparency, as a lack of understanding of model behavior can hinder trust and adoption. Future research should focus on developing robust frameworks for model interpretability and accountability to ensure responsible AI deployment in agriculture. This includes exploring further parallelization techniques and hardware configurations to enhance training efficiency and address communication bottlenecks [52].

7 Crop Monitoring Technologies

7.1 Remote Sensing Technologies

Remote sensing technologies are pivotal in modern crop monitoring, offering critical insights for precision agriculture through satellite imagery, aerial photography, and ground-based sensors. These technologies, when integrated with advanced computational tools like Large Language Models (LLMs) and Multimodal Large Models (MLLMs), enhance data processing and real-time decision-making [61]. Remote sensing allows rapid, large-scale data capture, providing comprehensive views of crop health and development. This capability is crucial for detecting spatial variability, enabling targeted interventions, optimizing resource allocation, and enhancing yields through high-throughput phenotyping and advanced machine learning [1, 63, 30]. Spectral imaging can identify stress factors such as nutrient deficiencies and pest infestations, which are not visible to the naked eye.

Recent advancements focus on improving data resolution and accuracy by integrating multiple data sources. High-resolution satellites and drones equipped with multispectral and hyperspectral sensors have significantly enhanced remote sensing precision, facilitating detailed monitoring of crop health and environmental changes critical for addressing food security and climate change [54, 63, 30]. These innovations support proactive management strategies by detecting subtle changes in crop health.

The integration of remote sensing data with machine learning and AI models, including LLMs and MLLMs, expands the potential of these technologies in crop monitoring. This integration enables predictive analytics frameworks that forecast crop performance and identify risks, enhancing agricultural resilience and sustainability [43]. Advancements in remote sensing technologies improve crop monitoring capabilities, supporting high-throughput phenotyping systems and facilitating the identification of phenotypic traits from large datasets. Consequently, these technologies enable stakeholders to address challenges like climate change and food security while optimizing breeding programs and resource management [30, 1]. By providing timely and accurate data, these technologies enhance informed decision-making and resource optimization, fostering more efficient and sustainable agricultural practices.

7.2 Internet of Things (IoT) in Agriculture

The Internet of Things (IoT) revolutionizes agriculture by offering innovative solutions for monitoring and managing farm operations. IoT devices, including sensors, drones, and smart irrigation systems, facilitate real-time data collection and analysis, enhancing decision-making processes and optimizing resource use. This integration improves precision agriculture by allowing continuous monitoring of environmental conditions, assessing crop health through high-throughput phenotyping, and automating farming activities with robotics and AI, addressing challenges like climate change and resource scarcity [1, 32, 51, 63, 30].

IoT applications in agriculture cover various aspects of farm management. For instance, IoT sensors monitor soil moisture, enabling precise irrigation scheduling to conserve water and enhance yields. Drones equipped with multispectral cameras survey fields, delivering data on crop health and

AI-generated, for reference only.

identifying pest or disease-affected areas. These drones use 3D point cloud analysis to improve plant health assessments, providing insights for timely crop management decisions [63, 51, 30]. This information allows targeted interventions, reducing blanket pesticide applications and minimizing environmental impact.

Moreover, IoT devices are vital in livestock management, tracking animal health and behavior. Wearable sensors monitor vital signs, detect illnesses early, and optimize feeding schedules, enhancing animal welfare and productivity. Integrating IoT with advanced data analytics and machine learning models improves the capability to anticipate and address agricultural challenges. By converting expert insights into quantifiable features with LLMs, farmers enhance predictive analytics and decision-making, incorporating nuanced domain knowledge for proactive farm management against crop diseases and environmental changes. Multimodal models like GPT-4V enrich understanding by analyzing diverse data sources, including satellite and ground-level images [16, 18, 80, 63, 30].

Deploying IoT technologies in agriculture presents challenges, including data security, connectivity issues, and the need for standardized protocols. Overcoming these challenges is vital for maximizing IoT's potential in revolutionizing agriculture, enhancing precision farming, and improving resource management, contributing to sustainable food production amid growing demands [1, 18, 15, 80, 63]. As IoT devices become more affordable and accessible, their adoption is expected to increase, driving innovations in precision agriculture and bolstering global food security and sustainability.

7.3 AI-Driven Analytics in Crop Monitoring

AI-driven analytics significantly enhance crop monitoring by providing advanced tools for data analysis and decision-making. These analytics utilize machine learning algorithms and AI models to process vast datasets from remote sensing technologies, IoT devices, and field observations. Integrating AI-driven analytics into crop monitoring improves the precision and timeliness of crop health assessments through high-quality ground truth data generated via advanced crowdsourcing techniques. This facilitates proactive management strategies that optimize resource utilization and improve yields. Researchers emphasize comprehensive databases and bioinformatics systems to analyze phenotypic traits, contributing to sustainable practices amid global challenges like climate change and food security [1, 30].

AI-driven analytics process complex datasets and derive actionable insights, enhancing predictive accuracy by incorporating expert domain knowledge through advanced models like LLMs. This integration transforms subjective insights into quantifiable features, improving risk assessment and decision-making across applications [18, 16]. Sophisticated algorithms enable AI models to identify patterns in crop data not apparent through traditional methods, allowing early detection of stress factors such as pest infestations and nutrient deficiencies. This capability enables targeted interventions, mitigating yield losses and enhancing crop resilience.

Furthermore, AI-driven analytics promote integrating diverse data types, including spectral imagery, weather data, and soil health metrics, providing a comprehensive view of crop conditions. This approach improves precision and reliability by leveraging advanced technologies like crowdsourced image analysis and high-throughput phenotyping. These innovations facilitate high-quality ground truth data collection, enabling effective management decisions. By integrating diverse data sources and employing automated systems, this methodology addresses plant phenomics complexities, supporting enhanced productivity and sustainability [1, 8, 63, 30]. AI models, including LLMs and MLLMs, further expand AI-driven analytics' potential by enabling multimodal data synthesis and improving complex agricultural systems' interpretability.

Ongoing advancements in AI-driven analytics propel innovations in crop monitoring, offering opportunities for enhancing productivity and sustainability. By providing timely insights into crop conditions, these analytics support data-driven decision-making and resource optimization, leading to more efficient practices. As AI technologies advance, their integration into crop monitoring is expected to increase, offering solutions for enhancing productivity and addressing food security challenges. This evolution includes developing high-throughput phenotyping systems leveraging AI for rapid data collection and analysis, facilitating precision breeding and agronomic trait identification. Methodologies like crowdsourced image analysis generate high-quality ground truth data, enhancing machine learning applications' accuracy in agriculture. As these technologies mature, they hold potential to revolutionize practices, addressing climate change, resource scarcity, and growing population demands [80, 30, 63, 1].

7.4 Impact on Real-Time Monitoring and Management

Integrating advanced technologies, including AI, IoT, and remote sensing, has transformed real-time monitoring and management in agriculture. These technologies enable data-driven decisions that optimize resource utilization, enhance crop management, and increase productivity by collecting and analyzing data from diverse sources like satellite imagery and sensor data. Multimodal foundation models like GPT-4V demonstrate capabilities in crop type identification and disease recognition, while crowdsourced image analysis generates high-quality ground truth data, supporting precision agriculture and improving food security amidst climate change and population growth [80, 18, 63, 30]. These technologies enable continuous data collection and analysis, providing a comprehensive view of agricultural systems that supports proactive management strategies.

AI-driven analytics, particularly those leveraging LLMs and MLLMs, are crucial for processing complex datasets and deriving actionable insights. These models excel in visual recognition, speech recognition, and logical reasoning, due to their capabilities in understanding and integrating information from multiple modalities. They transform domain-specific knowledge into quantifiable features, enhancing predictive analytics and decision-making accuracy. The effectiveness of these models is influenced by training data quality and quantity, highlighting the importance of a data-centric approach that prioritizes comprehensive dataset curation alongside model enhancements [25, 16]. These models facilitate multimodal data synthesis, offering a nuanced understanding of crop health and growth dynamics. Integrating and analyzing diverse data types in real-time allows early detection of stress factors and timely interventions, mitigating yield losses and enhancing crop resilience.

IoT devices enhance real-time monitoring by providing continuous data streams on soil moisture, weather conditions, and crop status. These devices enable precise control of irrigation and fertilization, optimizing resource use and reducing environmental impact. Integrating IoT with AI-driven analytics fosters sophisticated predictive models that forecast crop performance and identify risks, facilitating informed decision-making. This synergy allows systematic encoding of expert knowledge into quantifiable features, improving risk assessment and operational efficiency in agriculture. By leveraging advanced machine learning techniques, these models incorporate diverse data sources, providing actionable insights that optimize outcomes and promote sustainable practices [80, 18, 63, 16].

Remote sensing technologies, including satellite imagery and drone surveys, provide a comprehensive overview of landscapes by capturing spatial variability. These technologies identify specific areas needing intervention, enabling targeted management practices. Advancements in multimodal applications, including integrating large language models, enhance remote sensing data interpretation, allowing nuanced assessments of crop health, disease detection, and land cover classification, ultimately supporting improved decision-making and resource management [1, 54, 63, 44, 30]. High-resolution data from these technologies complements ground-based observations, providing comprehensive datasets that inform decisions. Real-time remote sensing data analysis supports precision agriculture practices, enhancing sustainability and productivity.

Integrating advanced technologies in real-time agricultural monitoring and management transforms the sector by enabling precise resource optimization and enhancing yields. Innovations in high-throughput phenotyping and data analytics allow rapid phenotypic trait collection and analysis, facilitating informed breeding program decisions and contributing to improved food security amid challenges like climate change and resource scarcity [30, 1]. By leveraging AI, IoT, and remote sensing capabilities, farmers can make informed decisions that enhance resilience and sustainability, contributing to global food security and environmental stewardship.

8 Conclusion

8.1 Challenges and Future Directions in AI Integration

The integration of AI into agriculture presents both significant opportunities and challenges, particularly in the deployment of Large Language Models (LLMs) and Multimodal Large Models (MLLMs). These models demand substantial computational resources, which can limit their accessibility and scalability in diverse agricultural settings. Advancing data processing systems for MLLMs is essential,

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with a focus on optimizing memory retrieval and reasoning capabilities, especially in environments with limited data availability. Additionally, developing robust evaluation methods for complex data types and expanding image corpora are crucial for improving model efficacy.

Ethical challenges, including biases in training data and the environmental impact of model development, require the establishment of comprehensive frameworks for ethical AI implementation in agriculture. This involves creating methodologies for bias detection and mitigation and exploring energy-efficient frameworks for Cross-Modal Retrieval (CMR) tasks. Enhancing decision-making through the study of metacognitive processes in LLMs can lead to more ethically aligned AI applications.

The specialization of multimodal models for agricultural purposes remains a key area for further research. Improving model efficiency, exploring additional data modalities, and refining training strategies will enhance their applicability. Creating specialized datasets for various crops and employing advanced machine learning techniques will advance plant phenomics applications.

Understanding the interaction between model capabilities and user needs is vital for developing more user-friendly AI solutions in agriculture. Enhancing interpretability, refining steering techniques, and addressing hallucination issues are critical steps in advancing AI integration. Moreover, integrating phenomics with other omics technologies offers a promising path for improving crop breeding outcomes. Future research should focus on this integration, explore new technologies, and address challenges related to environmental characterization to enhance agricultural productivity and sustainability. By tackling these challenges and pursuing these future directions, AI integration in agriculture can be optimized to promote more resilient and sustainable agricultural systems.

References

[1] Chunjiang Zhao, Ying Zhang, Jianjun Du, Xinyu Guo, Weiliang Wen, Shenghao Gu, Jinglu Wang, and Jiangchuan Fan. Crop phenomics: current status and perspectives. *Frontiers in Plant Science*, 10:714, 2019.

[2] Vahid Ashrafimoghari, Necdet Gürkan, and Jordan W. Suchow. Evaluating large language models on the gmat: Implications for the future of business education, 2024.

[3] Swapnaja Achintalwar, Adriana Alvarado Garcia, Ateret Anaby-Tavor, Ioana Baldini, Sara E. Berger, Bishwaranjan Bhattacharjee, Djallel Bouneffouf, Subhajit Chaudhury, Pin-Yu Chen, Lamogha Chiazor, Elizabeth M. Daly, Kirushikesh DB, Rogério Abreu de Paula, Pierre Dognin, Eitan Farchi, Soumya Ghosh, Michael Hind, Raya Horesh, George Kour, Ja Young Lee, Nishtha Madaan, Sameep Mehta, Erik Miehling, Keerthiram Murugesan, Manish Nagireddy, Inkit Padhi, David Piorkowski, Ambrish Rawat, Orna Raz, Prasanna Sattigeri, Hendrik Strobelt, Sarathkrishna Swaminathan, Christoph Tillmann, Aashka Trivedi, Kush R. Varshney, Dennis Wei, Shalisha Witherspooon, and Marcel Zalmanovici. Detectors for safe and reliable llms: Implementations, uses, and limitations, 2024.

[4] Humza Naveed, Asad Ullah Khan, Shi Qiu, Muhammad Saqib, Saeed Anwar, Muhammad Usman, Naveed Akhtar, Nick Barnes, and Ajmal Mian. A comprehensive overview of large language models. *arXiv preprint arXiv:2307.06435*, 2023.

[5] Bo He, Hengduo Li, Young Kyun Jang, Menglin Jia, Xuefei Cao, Ashish Shah, Abhinav Shrivastava, and Ser-Nam Lim. Ma-lmm: Memory-augmented large multimodal model for long-term video understanding, 2024.

[6] Jordan R Ubbens and Ian Stavness. Deep plant phenomics: a deep learning platform for complex plant phenotyping tasks. *Frontiers in plant science*, 8:1190, 2017.

[7] Marcos Egea-Cortines and John H Doonan. Phenomics, 2018.

[8] A Shashko, U Bandarenka, U Svetlakou, NL Pshybyto, II Smolich, AI Sokolik, and V Demidchik. Basic principles and main applications of plant phenomics. *Advances in Biology & Earth Sciences*, 6(1), 2021.

[9] Ratnakumar Pasala and Brij Bihari Pandey. Plant phenomics: High-throughput technology for accelerating genomics. *Journal of Biosciences*, 45(1):111, 2020.

[10] Denis Havlik and Marcelo Pias. Common errors in generative ai systems used for knowledge extraction in the climate action domain, 2024.

[11] Muhammad Usman Hadi, Rizwan Qureshi, Abbas Shah, Muhammad Irfan, Anas Zafar, Muhammad Bilal Shaikh, Naveed Akhtar, Jia Wu, Seyedali Mirjalili, et al. A survey on large language models: Applications, challenges, limitations, and practical usage. *Authorea Preprints*, 3, 2023.

[12] Yilun Zhao, Haowei Zhang, Shengyun Si, Linyong Nan, Xiangru Tang, and Arman Cohan. Investigating table-to-text generation capabilities of llms in real-world information seeking scenarios, 2023.

[13] Kaiyu Huang, Fengran Mo, Xinyu Zhang, Hongliang Li, You Li, Yuanchi Zhang, Weijian Yi, Yulong Mao, Jinchen Liu, Yuzhuang Xu, Jinan Xu, Jian-Yun Nie, and Yang Liu. A survey on large language models with multilingualism: Recent advances and new frontiers, 2025.

[14] Junfeng Jiao, Saleh Afroogh, Yiming Xu, and Connor Phillips. Navigating llm ethics: Advancements, challenges, and future directions, 2024.

[15] Jesse G Meyer, Ryan J Urbanowicz, Patrick CN Martin, Karen O'Connor, Ruowang Li, Pei-Chen Peng, Tiffani J Bright, Nicholas Tatonetti, Kyoung Jae Won, Graciela Gonzalez-Hernandez, et al. Chatgpt and large language models in academia: opportunities and challenges. *BioData Mining*, 16(1):20, 2023.

[16] Phoebe Jing, Yijing Gao, Yuanhang Zhang, and Xianlong Zeng. Translating expert intuition into quantifiable features: Encode investigator domain knowledge via llm for enhanced predictive analytics, 2024.

[17] Shabnam Hassani. Enhancing legal compliance and regulation analysis with large language models, 2024.

[18] Q. Vera Liao and Jennifer Wortman Vaughan. Ai transparency in the age of llms: A human-centered research roadmap, 2023.

[19] Dmitry Scherbakov, Nina Hubig, Vinita Jansari, Alexander Bakumenko, and Leslie A. Lenert. The emergence of large language models (llm) as a tool in literature reviews: an llm automated systematic review, 2024.

[20] Gustavo A Lobos, Anyela V Camargo, Alejandro Del Pozo, Jose L Araus, Rodomiro Ortiz, and John H Doonan. Plant phenotyping and phenomics for plant breeding, 2017.

[21] Saurabh Pahune and Manoj Chandrasekharan. Several categories of large language models (llms): A short survey. *arXiv preprint arXiv:2307.10188*, 2023.

[22] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 2023.

[23] Samuel R Bowman. Eight things to know about large language models. *arXiv preprint arXiv:2304.00612*, 2023.

[24] Shengsheng Qian, Zuyi Zhou, Dizhan Xue, Bing Wang, and Changsheng Xu. From linguistic giants to sensory maestros: A survey on cross-modal reasoning with large language models, 2024.

[25] Tianyi Bai, Hao Liang, Binwang Wan, Yanran Xu, Xi Li, Shiyu Li, Ling Yang, Bozhou Li, Yifan Wang, Bin Cui, et al. A survey of multimodal large language model from a data-centric perspective. *arXiv preprint arXiv:2405.16640*, 2024.

[26] Marcin P. Joachimiak, Mark A. Miller, J. Harry Caufield, Ryan Ly, Nomi L. Harris, Andrew Tritt, Christopher J. Mungall, and Kristofer E. Bouchard. The artificial intelligence ontology: Llm-assisted construction of ai concept hierarchies, 2024.

[27] S. M Towhidul Islam Tonmoy, S M Mehedi Zaman, Vinija Jain, Anku Rani, Vipula Rawte, Aman Chadha, and Amitava Das. A comprehensive survey of hallucination mitigation techniques in large language models, 2024.

[28] Sen Huang, Kaixiang Yang, Sheng Qi, and Rui Wang. When large language model meets optimization, 2024.

[29] François Vasseur, Denis Cornet, Grégory Beurier, Julie Messier, Lauriane Rouan, Justine Bresson, Martin Ecarnot, Mark Stahl, Simon Heumos, Marianne Gérard, et al. A perspective on plant phenomics: coupling deep learning and near-infrared spectroscopy. *Frontiers in plant science*, 13:836488, 2022.

[30] Naihui Zhou, Zachary D Siegel, Scott Zarecor, Nigel Lee, Darwin A Campbell, Carson M Andorf, Dan Nettleton, Carolyn J Lawrence-Dill, Baskar Ganapathysubramanian, Jonathan W Kelly, et al. Crowdsourcing image analysis for plant phenomics to generate ground truth data for machine learning. *PLoS computational biology*, 14(7):e1006337, 2018.

[31] Gota Morota, Diego Jarquin, Malachy T. Campbell, and Hiroyoshi Iwata. Statistical methods for the quantitative genetic analysis of high-throughput phenotyping data, 2019.

[32] Javier Rodriguez-Sanchez, Kyle Johnsen, and Changying Li. A ground mobile robot for autonomous terrestrial laser scanning-based field phenotyping, 2024.

[33] Mukesh Kumar Vishal, Dipesh Tamboli, Abhijeet Patil, Rohit Saluja, Biplab Banerjee, Amit Sethi, Dhandapani Raju, Sudhir Kumar, R N Sahoo, Viswanathan Chinnusamy, and J Adinarayana. Image-based phenotyping of diverse rice (oryza sativa l.) genotypes, 2020.

[34] Sergey Nesteruk, Dmitrii Shadrin, and Mariia Pukalchik. Image augmentation for multitask few-shot learning: Agricultural domain use-case, 2021.

AI-generated, for reference only.

[35] Tianyi Chen, Tianyu Ding, Badal Yadav, Ilya Zharkov, and Luming Liang. Lorashear: Efficient large language model structured pruning and knowledge recovery, 2023.

[36] Tao Fan, Yan Kang, Guoqiang Ma, Weijing Chen, Wenbin Wei, Lixin Fan, and Qiang Yang. Fate-llm: A industrial grade federated learning framework for large language models, 2023.

[37] Dimitrios Michael Manias, Ali Chouman, and Abdallah Shami. Semantic routing for enhanced performance of llm-assisted intent-based 5g core network management and orchestration, 2024.

[38] Zelong Li, Shuyuan Xu, Kai Mei, Wenyue Hua, Balaji Rama, Om Raheja, Hao Wang, He Zhu, and Yongfeng Zhang. Autoflow: Automated workflow generation for large language model agents, 2024.

[39] Xu Guo and Yiqiang Chen. Generative ai for synthetic data generation: Methods, challenges and the future, 2024.

[40] Weihao Yu, Zhengyuan Yang, Linjie Li, Jianfeng Wang, Kevin Lin, Zicheng Liu, Xinchao Wang, and Lijuan Wang. Mm-vet: Evaluating large multimodal models for integrated capabilities. *arXiv preprint arXiv:2308.02490*, 2023.

[41] Zhiqi Ge, Hongzhe Huang, Mingze Zhou, Juncheng Li, Guoming Wang, Siliang Tang, and Yueting Zhuang. Worldgpt: Empowering llm as multimodal world model. In *Proceedings of the 32nd ACM International Conference on Multimedia*, pages 7346–7355, 2024.

[42] Qian Niu, Keyu Chen, Ming Li, Pohsun Feng, Ziqian Bi, Lawrence KQ Yan, Yichao Zhang, Caitlyn Heqi Yin, Cheng Fei, Junyu Liu, Benji Peng, Tianyang Wang, Yunze Wang, Silin Chen, and Ming Liu. From text to multimodality: Exploring the evolution and impact of large language models in medical practice, 2024.

[43] Conghui He, Zhenjiang Jin, Chao Xu, Jiantao Qiu, Bin Wang, Wei Li, Hang Yan, Jiaqi Wang, and Dahua Lin. Wanjuan: A comprehensive multimodal dataset for advancing english and chinese large models, 2023.

[44] Junyao Ge, Xu Zhang, Yang Zheng, Kaitai Guo, and Jimin Liang. Rsteller: Scaling up visual language modeling in remote sensing with rich linguistic semantics from openly available data and large language models, 2025.

[45] Alejandro Tlaie. Exploring and steering the moral compass of large language models, 2024.

[46] Jiayang Wu, Wensheng Gan, Zefeng Chen, Shicheng Wan, and S Yu Philip. Multimodal large language models: A survey. In *2023 IEEE International Conference on Big Data (BigData)*, pages 2247–2256. IEEE, 2023.

[47] Wanjuan: A comprehensive multimo.

[48] Muhammad Arbab Arshad, Talukder Zaki Jubery, Tirtho Roy, Rim Nassiri, Asheesh K. Singh, Arti Singh, Chinmay Hegde, Baskar Ganapathysubramanian, Aditya Balu, Adarsh Krishnamurthy, and Soumik Sarkar. Ageval: A benchmark for zero-shot and few-shot plant stress phenotyping with multimodal llms, 2024.

[49] Koji Noshita, Hidekazu Murata, and Shiryu Kirie. Model-based plant phenomics on morphological traits using morphometric descriptors. *Breeding Science*, 72(1):19–30, 2022.

[50] Shiva Azimi and Tapan K. Gandhi. Performance comparison of 3d correspondence grouping algorithm for 3d plant point clouds, 2019.

[51] Shiva Azimi, Brejesh lall, and Tapan K. Gandhi. Performance evalution of 3d keypoint detectors and descriptors for plants health classification, 2019.

[52] Jared Fernandez, Luca Wehrstedt, Leonid Shamis, Mostafa Elhoushi, Kalyan Saladi, Yonatan Bisk, Emma Strubell, and Jacob Kahn. Hardware scaling trends and diminishing returns in large-scale distributed training, 2024.

[53] Christophe Pradal, Simon Artzet, Jerome Chopard, Dimitri Dupuis, Christian Fournier, Michael Mielewczik, Vincent Negre, Pascal Neveu, Didier Parigot, Patrick Valduriez, et al. Infraphenogrid: a scientific workflow infrastructure for plant phenomics on the grid. *Future Generation Computer Systems*, 67:341–353, 2017.

[54] Dilxat Muhtar, Zhenshi Li, Feng Gu, Xueliang Zhang, and Pengfeng Xiao. Lhrs-bot: Empowering remote sensing with vgi-enhanced large multimodal language model, 2024.

[55] Jinxiang Lai, Jie Zhang, Jun Liu, Jian Li, Xiaocheng Lu, and Song Guo. Spider: Any-to-many multimodal llm, 2024.

[56] Qinghao Ye, Haiyang Xu, Jiabo Ye, Ming Yan, Anwen Hu, Haowei Liu, Qi Qian, Ji Zhang, and Fei Huang. mplug-owl2: Revolutionizing multi-modal large language model with modality collaboration. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13040–13051, 2024.

[57] Xuying Li, Zhuo Li, Yuji Kosuga, Yasuhiro Yoshida, and Victor Bian. Precision knowledge editing: Enhancing safety in large language models, 2024.

[58] Rana Muhammad Shahroz Khan, Pingzhi Li, Sukwon Yun, Zhenyu Wang, Shahriar Nirjon, Chau-Wai Wong, and Tianlong Chen. Portllm: Personalizing evolving large language models with training-free and portable model patches, 2024.

[59] Gaurav Singh and Kavitesh Kumar Bali. Enhancing decision-making in optimization through llm-assisted inference: A neural networks perspective, 2024.

[60] Chi Chen, Yiyang Du, Zheng Fang, Ziyue Wang, Fuwen Luo, Peng Li, Ming Yan, Ji Zhang, Fei Huang, Maosong Sun, et al. Model composition for multimodal large language models. *arXiv preprint arXiv:2402.12750*, 2024.

[61] Henry Hengyuan Zhao, Pan Zhou, and Mike Zheng Shou. Genixer: Empowering multimodal large language model as a powerful data generator. In *European Conference on Computer Vision*, pages 129–147. Springer, 2024.

[62] Qinghao Ye, Haiyang Xu, Guohai Xu, Jiabo Ye, Ming Yan, Yiyang Zhou, Junyang Wang, Anwen Hu, Pengcheng Shi, Yaya Shi, et al. mplug-owl: Modularization empowers large language models with multimodality. *arXiv preprint arXiv:2304.14178*, 2023.

[63] Chenjiao Tan, Qian Cao, Yiwei Li, Jielu Zhang, Xiao Yang, Huaqin Zhao, Zihao Wu, Zhengliang Liu, Hao Yang, Nemin Wu, Tao Tang, Xinyue Ye, Lilong Chai, Ninghao Liu, Changying Li, Lan Mu, Tianming Liu, and Gengchen Mai. On the promises and challenges of multimodal foundation models for geographical, environmental, agricultural, and urban planning applications, 2023.

[64] Ge Zhang, Scott Qu, Jiaheng Liu, Chenchen Zhang, Chenghua Lin, Chou Leuang Yu, Danny Pan, Esther Cheng, Jie Liu, Qunshu Lin, Raven Yuan, Tuney Zheng, Wei Pang, Xinrun Du, Yiming Liang, Yinghao Ma, Yizhi Li, Ziyang Ma, Bill Lin, Emmanouil Benetos, Huan Yang, Junting Zhou, Kaijing Ma, Minghao Liu, Morry Niu, Noah Wang, Quehry Que, Ruibo Liu, Sine Liu, Shawn Guo, Soren Gao, Wangchunshu Zhou, Xinyue Zhang, Yizhi Zhou, Yubo Wang, Yuelin Bai, Yuhan Zhang, Yuxiang Zhang, Zenith Wang, Zhenzhu Yang, Zijian Zhao, Jiajun Zhang, Wanli Ouyang, Wenhao Huang, and Wenhu Chen. Map-neo: Highly capable and transparent bilingual large language model series, 2024.

[65] Fouad Trad and Ali Chehab. Evaluating the efficacy of prompt-engineered large multimodal models versus fine-tuned vision transformers in image-based security applications, 2024.

[66] Andrei Cosmin Redis, Mohammadreza Fani Sani, Bahram Zarrin, and Andrea Burattin. Processtbench: An llm plan generation dataset for process mining, 2024.

[67] Muhammed Saeed, Elgizouli Mohamed, Mukhtar Mohamed, Shaina Raza, Muhammad Abdul-Mageed, and Shady Shehata. Desert camels and oil sheikhs: Arab-centric red teaming of frontier llms, 2024.

[68] Emily Reif, Minsuk Kahng, and Savvas Petridis. Visualizing linguistic diversity of text datasets synthesized by large language models, 2023.

[69] Wei Wang, Zhichao Hou, Xiaorui Liu, and Xinxia Peng. Exploring the potentials and challenges of using large language models for the analysis of transcriptional regulation of long non-coding rnas, 2024.

[70] Zhi Jing, Yongye Su, Yikun Han, Bo Yuan, Haiyun Xu, Chunjiang Liu, Kehai Chen, and Min Zhang. When large language models meet vector databases: A survey, 2024.

[71] Junhao Zheng, Shengjie Qiu, Chengming Shi, and Qianli Ma. Towards lifelong learning of large language models: A survey, 2024.

[72] Ryan Burnell, Han Hao, Andrew R. A. Conway, and Jose Hernandez Orallo. Revealing the structure of language model capabilities, 2023.

[73] Ruyi Gan, Ziwei Wu, Renliang Sun, Junyu Lu, Xiaojun Wu, Dixiang Zhang, Kunhao Pan, Junqing He, Yuanhe Tian, Ping Yang, Qi Yang, Hao Wang, Jiaxing Zhang, and Yan Song. Ziya2: Data-centric learning is all llms need, 2024.

[74] Nicholas Lee, Thanakul Wattanawong, Sehoon Kim, Karttikeya Mangalam, Sheng Shen, Gopala Anumanchipalli, Michael W. Mahoney, Kurt Keutzer, and Amir Gholami. Llm2llm: Boosting llms with novel iterative data enhancement, 2024.

[75] Xingjin Wang, Linjing Li, and Daniel Zeng. Ldm^2: A large decision model imitating human cognition with dynamic memory enhancement, 2023.

[76] Vu-Thuan Doan, Quoc-Truong Truong, Duc-Vu Nguyen, Vinh-Tiep Nguyen, and Thuy-Ngan Nguyen Luu. Efficient finetuning large language models for vietnamese chatbot, 2023.

[77] Hongliang He, Jinfeng Huang, Qi Li, Xu Wang, Feibin Zhang, Kangding Yang, Li Meng, and Fulei Chu. Maintagt:sim2real-guided multimodal large model for intelligent maintenance with chain-of-thought reasoning, 2024.

[78] Duzhen Zhang, Yahan Yu, Jiahua Dong, Chenxing Li, Dan Su, Chenhui Chu, and Dong Yu. Mm-llms: Recent advances in multimodal large language models. *arXiv preprint arXiv:2401.13601*, 2024.

[79] Vishvak Murahari, Ameet Deshpande, Peter Clark, Tanmay Rajpurohit, Ashish Sabharwal, Karthik Narasimhan, and Ashwin Kalyan. Qualeval: Qualitative evaluation for model improvement, 2024.

[80] Frank Joublin, Antonello Ceravola, Joerg Deigmoeller, Michael Gienger, Mathias Franzius, and Julian Eggert. A glimpse in chatgpt capabilities and its impact for ai research, 2023.

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