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Smart Agro-ecosystem: A Review of LLM-based Robotic Systems for Sensing and Decision Support in Precision Agriculture

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Abstract

Smart agriculture employs emerging technologies to address main challenges such as greenhouse gases emissions, crop yield optimization, and efficient irrigation through optimized resource planning. This paper reviews Large Language Models (LLMs), robots, and multi-sensor data fusion by combining information from multiple sensors to detect real-time gas emissions for decision support in Agricultural Cyber Physical System (ACPS). LLMs are distinct from earlier AI because they understand context and can process data from IoT sensors, drones, and satellites into useful advice for farmers. Robots with gas sensors can effectively monitor the emissions such as CO2, CH4, NH3, and NO2, while adaptive algorithms improve resilience under dynamic field conditions. This paper systematically reviews the current trends in LLM-based natural language processing (NLP) systems, multimodal architectures, and fusion strategies for distributed intelligence. Some case studies are used to demonstrate practical scenarios within the ACPS domain, highlighting AI deployment benefits, e.g. improved environmental parameters and better compliance with climate regulations. Future directions include swarm robotics for scalable monitoring, edge AI for real-time inference and lightweight LLMs for resource-constrained embedded cyber-physical systems. By compiling state-of-the-art research, this review establishes a road-map for LLM-driven, robotics-enabled ecosystem offering transformative potential for climate-smart, resilient agriculture.

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1. Introduction

Artificial Intelligence (AI) is transforming agricultural technology (Agritech) by enabling data-driven learning and decision-making for an efficient Agri-ecosystem by analyzing sensor data obtained from drones, satellites and IOT devices. The purpose is to monitor air pollutants, crop health, soil conditions and greenhouse gases (GHG), supporting optimized irrigation, fertilization, and pest-management within an ACPS. Some interesting features of LLM-powered ACPS includes autonomous farming, predictive analytics, and resource management to enhance productivity and reduced wastes. Recently, many researchers proposed AI-based

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approaches for Agriculture. For example, Nagireddy reviewed sensor-driven autonomy in agriculture, highlighting the integration of cameras, LiDAR, and radar for precision farming and multimodal perception using sensor fusion. Some key advantages of the framework include autonomous navigation within the farm, precision irrigation, robotic harvesting, and input management, improving efficiency, resource conservation, and crop yields. However, these benefits are not without a price. The technical challenges include sensor durability, data handling, and added costs, especially for small farms. Despite these factors, edge computing, machine learning, and collaborative ownership models are accelerating adoption of technology within Agroecosystem required to create sustainable, data-driven, climate-resilient agricultural systems [1]. Wah, 2025 reviewed the transformative role of AI and IoT in advancing precision, resource optimized and sustainable agriculture in Malaysia. The study highlights AI-assisted irrigation, surveillance and crops monitoring using an IoT system that improve crop yield, water efficiency, and operational performance. Even in the presence of barriers for smallholder adoption, such as cost and technical training, the authors suggest a government assisted support program to initiate digital literacy programs, and assit in the foundation of scalable AI solutions for real-world applications including hyper-spectral imaging for rice farming and block-chain for food traceability. The review calls for cross-sector collaboration, adaptive regulation, and inclusive innovation to achieve a climate resilient, smart agricultural sector in the country [2]. Gryshova et al., 2024 highlighted the transformative potential of AI in Climate-Smart Agriculture (CSA), with prime emphasis on sustainable and resilient farming practices by promoting AI applications for crop, live-stock, and aquaculture management, as well as landscape and ecosystem monitoring, in order to optimize productivity while mitigating climate risks. AI-driven tools are found to enhance the impact of remote sensing algorithms enabling precision farming, climate modeling, crop monitoring, and early intervention for pest and disease control. The authors highlighted the significance of data integration and collaborative decision support to promote AI benefits even to small scale farms. In summary, Gryshova et al. concluded that AI can effectively enhance resource efficiency to ensure sustainable and climate resilient agricultural practices via intelligent decision-making, thus supporting global food security [3]. Among the various AI methods, LLMs have been found to have revolutionary potential for smart farming applications, enhancing automation and sustainability. These advantages are achieved by enabling intelligent interpretation of complex datasets as LLMs provide actionable insights and decision support, helping farmers to optimize resource management, predictive analytics, and sustainable agricultural practices which is the primary aim of this review paper. Therefore, we seek to critically review and synthesize the role of LLMs in smart agriculture, via integration with robotics and multi-sensor data fusion for gas detection and decision support. This review aligns with a critical research gap which has not been comprehensively explored in previous studies, i.e. the integration of AI/LLMs, robotics, and sensor fusion altogether in an agricultural CPS. The rationale lies in the timely assessment for data-driven solutions to successfully reduce greenhouse gas (GHG) emissions and enhance resilience and sustainability. By blending state-of-the-art farming approaches with LLM driven AI tools, this review provides the state-of-the-art as well as a futuristic perspective for the next-generation smart agro-ecosystem. This review is organized as follows: Section 2 introduces the theoretical background of LLMs and their role in modernizing agriculture. Section 3 explores the integration of LLMs with robotics and embedded sensor technologies. Section 4 presents case studies and real-world implementations, and discusses the operational benefits and key limitations of LLM technology. Section 5 describes the broader challenges along with the mitigation strategies. Finally, Section 6 summarizes the possible future research avenues to assess the impact of LLM-driven high-tech robots that can shape the present arena into an adaptive and sustainable agricultural ecosystem. Unlike existing review studies that typically focus on isolated aspects such as AI in agriculture, agricultural robotics, or sensor-based monitoring, this work provides an integrated perspective by combining LLM-driven reasoning, robotic sensing platforms, and multi-sensor data fusion for environmental gas monitoring within agricultural cyber-physical systems (ACPS).

2. Systemic Review and Analysis

The initial step of this review was to select articles from different scientific databases such as Scopus, Google Scholar, Web of science, IEEE, PubMed and ScienceDirect after that the process of eliminating duplicated articles was carried out. 83 studies in total addressing LLM-integrated agricultural ecosystems were selected and the presence of a distinct temporal trend was noted as the titles and abstracts were screened for inclusions as irrelevant studies and fitness of the full studies was assessed. Until 2020, there are only 4 published papers, and most of the papers (79% or 95%) were published from and after 2020, due to the advent of powerful LLMs, such as GPT and its variants, BERT and its variants, with highest numbers of publications between 2023 and 2025. The publications chosen were mainly journal articles (67.5%), with preprints (19.3%), conference papers (8.4%) and thesis or book chapters (4.8%). With the aim of defining the intersections and interconnections among domains, three clusters were found: 35 studies show how LLMs can be key engines for reasoning and decision-making capabilities in robotics; 28 studies highlight the importance of environmental sensing and mobility in robotics, and 20 studies reveal an emphasis on human–AI interaction, with a particular focus on conversational agents, explainable AI, and translating technical findings into practical recommendations. Interestingly, the differences in common standards or benchmarks were listed among the research gaps, while deployment on edge, compatibility with real world scenarios for resilience testing, and integration of agronomic and environmental know-how were all cited as future research steps. The literature survey demonstrates that there is a noteworthy change from loose technologies towards integrated and LLM based Agricultural CPS, which on the back of scalpable, intelligent and climate-smart embedded farming solutions makes sense. The literature survey historically displayed in Fig.1 is very important as a base of the development of LLM in the agriculture sector. Regarding the systematic review, things were done with a methodical rigor: protocol of selection. First, rough searches were made in the databases and the records were initially screened based on specific inclusion criteria, for example, related to LLM integration in agriculture, sensing based on robotics, multi-sensor data fusion within agricultural cyber-physical systems. Studies which were not technically relevant or had no experimental validation or were confined to non-related field were excluded. In addition, a qualitative assessment of selected studies was conducted, taking into account the aspects such as publication type, the way in which the method was applied and the clarity of the method. A formal diagram (PRISMA style) was not strictly observed, but a selection process was followed, which involved ensuring that literature selected were technically relevant, consistent and transparent.

3. Advantages of Large Language Models (LLMs)

The primary innovation of this review lies in bridging three traditionally separate research domains—LLMs, robotic sensing systems, and agricultural data fusion—into a unified conceptual framework. While prior studies have explored these components independently, their combined role in enabling intelligent, context-aware, and adaptive agricultural decision-making has not been sufficiently addressed. LLMs are advanced AI algorithms that learn patterns when trained on vast text datasets enabling them to understand, generate, and reason with human-like language using transformer architectures [4]. They are widely used for tasks such as summarizing text, translating from one language to another, chatbots, content creation, code generation, and problem-solving across various domains; such as healthcare, finance, education, customer service, robotics, and agriculture by mimicking humans [5]. Among these areas, agriculture and food security has recently received significant attention of the research community due to its growing importance and the need for intelligent, data-driven solutions [6]. LLMs are increasingly required in agriculture to convert complex data (weather, soil, sensors, drones) into simple, actionable decisions/commands for farmers who are not aware of the complex technical data and statistical inferences [7]. This expert-level guidance to farmers is available 24/7, even in remote areas, which enhances precision farming by optimising water, fertiliser, and pest management. Thus, improving agro-ecosystem's predictability, sustainability, and profitability [8, 9]. The history of using LLM in agriculture is compiled in Figure 2, which shows the pre-2020 agriculture technology relying on traditional-AI and machine learning models for yield prediction, pest detection, and weather forecasting, while LLMs were not applied, and NLP usage was limited to theoretical models and research papers only.

Between 2020 and 2022, LLMs like GPT-3 began to be applied in the real world, where they are deployed to summarise the agricultural data, answer farmers' queries, and analyse research literature, though applications were mostly experimental. During 2023 - 2024, LLMs expanded into advisory systems to provide crop management, fertilizer recommendations, pest and disease identification via IoT sensors to ensure sustainability. From 2025 to the present, LLMs are integrated within ACPS, including mobile robots, drones, and sensors to interpret real-time data and guide precision irrigation, greenhouse automation, livestock monitoring, and greenhouse gas analysis. Looking ahead in future tech pathways, LLMs are expected to serve as the "brain" of fully autonomous smart farms, enabling climate-smart agriculture, supply chain optimization, and enhanced global food security in the coming decade [10–14]. While LLM-based decision making can offer benefits, challenges arise when attempting to deploy them in real-time systems, such as robotic systems, including those of computational latency. To overcome this, there are some hybrid designs that use lightweight edge models for time vital tasks and computationally demanding reasoning is outsourced to a cloud based LLM. Edge AI techniques like model compression and quantization can be used for a partial deployment of LLM capabilities on embedded devices and achieve faster responses. Moreover, the use of asynchrony in communication and caching in pipelines can help reduce latencies, ensuring timely delivery of responses to dynamic requirements in agriculture. All

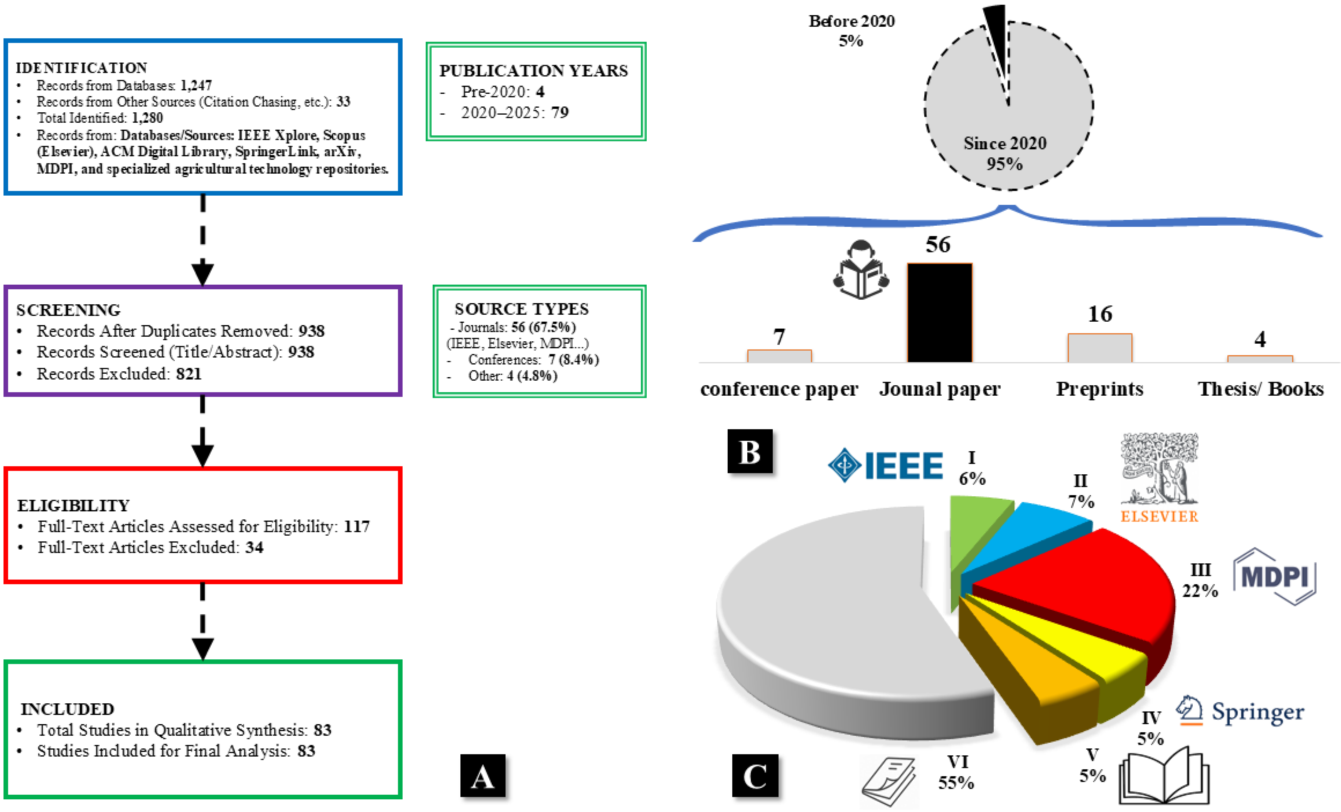

Figure 1. Systematic literature review protocol

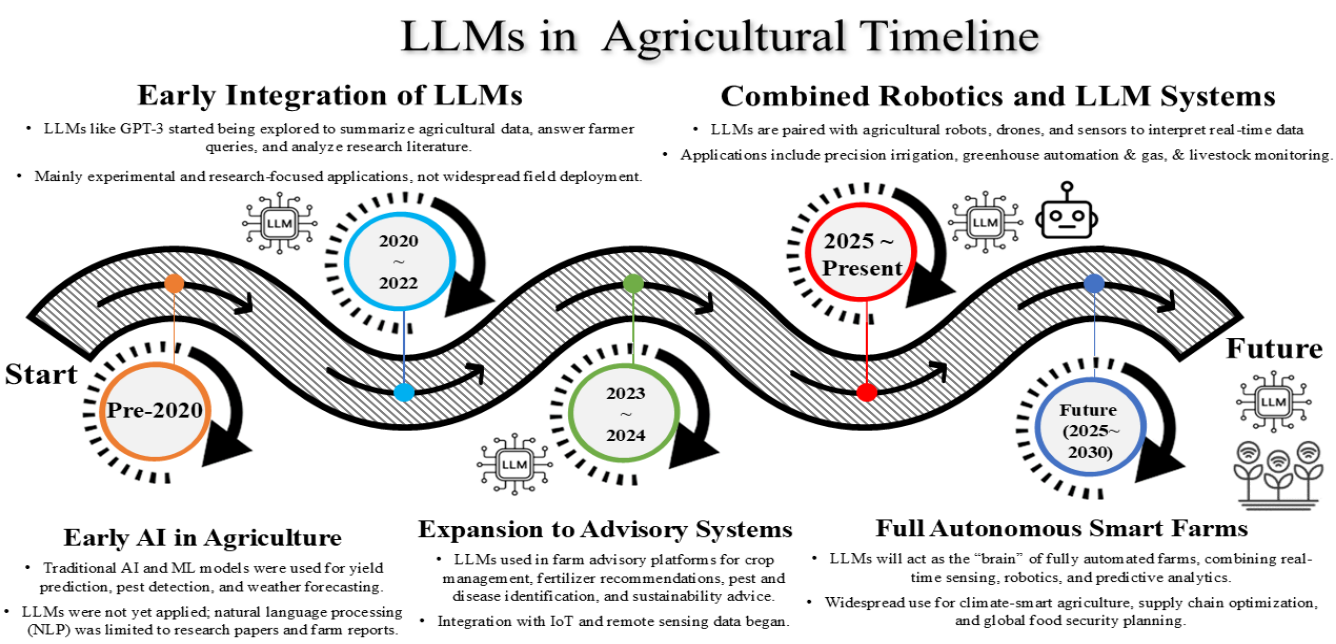

Figure 2. Historical evolution of LLMs in agriculture

these strategies make it possible to practically implement LLMs in real-time robotic systems. LLM timeline depicts that a wide range of agricultural activities are benefiting from it as summarized in Figure 3. As noticed from the flowchart, LLMs act as intelligent advisors, transforming complex agricultural data into actionable tasks to enhance productivity and sustainability [15, 16]. Inside the LLM model, the first block converts the input text into tokens, followed by the second block that transforms these tokens into embedding, while adding positional encoding to maintain word order in the subsequent block. The encoded inputs then pass-through multiple transformer layers containing self-attention and feed-forward networks to learn contextual and semantic patterns. Finally, the hidden states are then processed by an output layer to predict the next token, and the entire model is trained through pre-training, fine-tuning, and instruction tuning to generate accurate and coherent responses [17].

3.1. LLM application framework for Smart Agriculture

Designing an LLM for agricultural CPS depends on the nature of the task it is intended to perform, such as soil management advice, crop recommendations, pest detection, and yield prediction [18]. A general framework of LLM applications in smart farming is shown in Figure 4. The model takes structured data inputs (e.g., text from recommended guidelines, research papers, reports, farmer queries, and weather forecasts) and structured data such as soil parameters, wind data, temperature and humidity, crop type, and pesticide usage, with optional integration of images or sensor data for multi-modal applications. Inputs are preprocessed through tokenization for text and normalization or encoding for structured data, and categorical features like crop types are converted into embeddings. These inputs are transformed into dense vector representations through embeddings, including text embeddings, numerical embeddings for continuous variables, and categorical embeddings for crop, soil, or pest types where the core of the model consists of stacked transformer layers with self-attention mechanisms that capture relationships among input features and multi-head attention to focus on multiple aspects simultaneously. Task-specific heads are added depending on the application, such as classification heads for crop recommendation or pest prediction, regression heads for yield prediction or fertilizer advice, and decoder or generative heads for text summarization or question answering. The model is trained on agricultural datasets, which may include multilingual reports, sensor readings, weather data, and satellite imagery, using appropriate loss functions like cross-entropy for classification, MSE or MAE for regression, or weighted sums for multitask learning, and can be fine-tuned from a pre-trained LLM. Optionally, multi-modal integration with vision models can be used for tasks like crop disease detection or soil analysis, using early or late fusion [19]. In real world agriculture applications, there are challenge issues of data heterogeneity and incompleteness. To overcome the above problem, the proposed framework adopts pre-processing and fusion mechanisms, which can flexibly combine the multi-source information. Imputation techniques, adaptive filtering or uncertainty-aware models that assign the confidence value on each input source can be used to deal with missing or noisy sensor readings. Furthermore, multimodal fusion strategies like late and hybrid fusion that enable separate processing of each data stream before their fusion can be employed to overcome the problems caused by incomplete data sets. This guarantees that the decision-making pipeline is strong even in presence of realistic conditions such as sensors failures, delays in communicating with the sensors, or noise and interference in the environment.

Training LLMs in agriculture requires a diverse and multi-modal dataset using textual information such as research papers, agricultural reports, farmer queries, manuals, and weather forecasts; structured farm data including crop types, soil parameters, weather measurements, pest and disease records, and resource usage; sensor and IoT data from soil and environmental sensors; as well as remote sensing imagery from satellites and UAVs for crop health monitoring. In addition, economic data as well as multilingual regional content improve the generalizability and applicability of the model by using proper annotation for disease recognition and classification, yield estimation, and crop recommendations ensure actionable outputs. With the deployment of a mixture of such resources, LLMs should offer predictive analysis, guidance, and decision analytics on the optimization of yields even at a smaller scale due to the integration of advanced sensing technologies, robotized agriculture is more accurate thanks to the reliability of data collection, and accurate geo-location applications made possible by the use of machine learning and data analytics applications which in its turn help interpret this data in order to make a timely decisions. The apothexy of agritech implementation chain is supported by LLM, which can not only be used for field calibration but also for the continuous monitoring of the performance of these ingredients to ensure consistency in staff planning and utilization, better crop management and increased productivity regardless of the seasonality throughout the year [20]. An online literature review to discuss the role of the AI/LLM solution in agricultural operations showed that the AI/LLM building blocks had the potential to convert the standard practices into smart farming by enhancing the operative viability, while necessitating massive volumes of labelled data to train the model. Maybe a profound understanding of the literature will provide numerous applications where agriculture 5.0 would have been superior compared to precision farming. The former enables not only

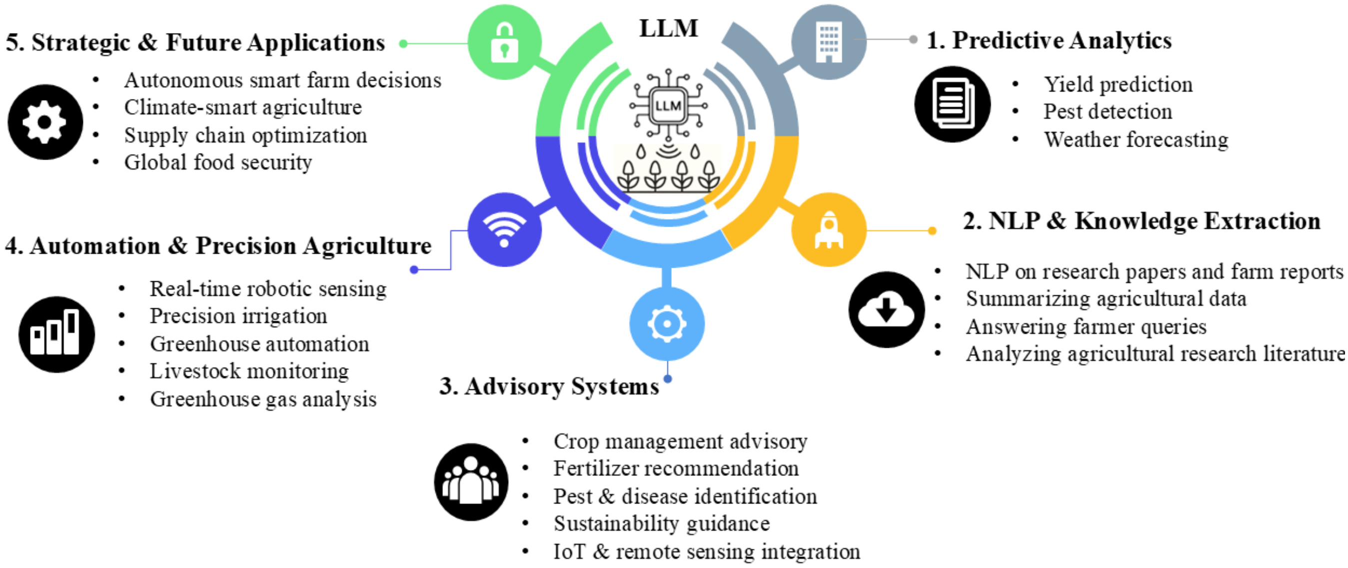

Figure 3. LLM based applications in Agricultural technology

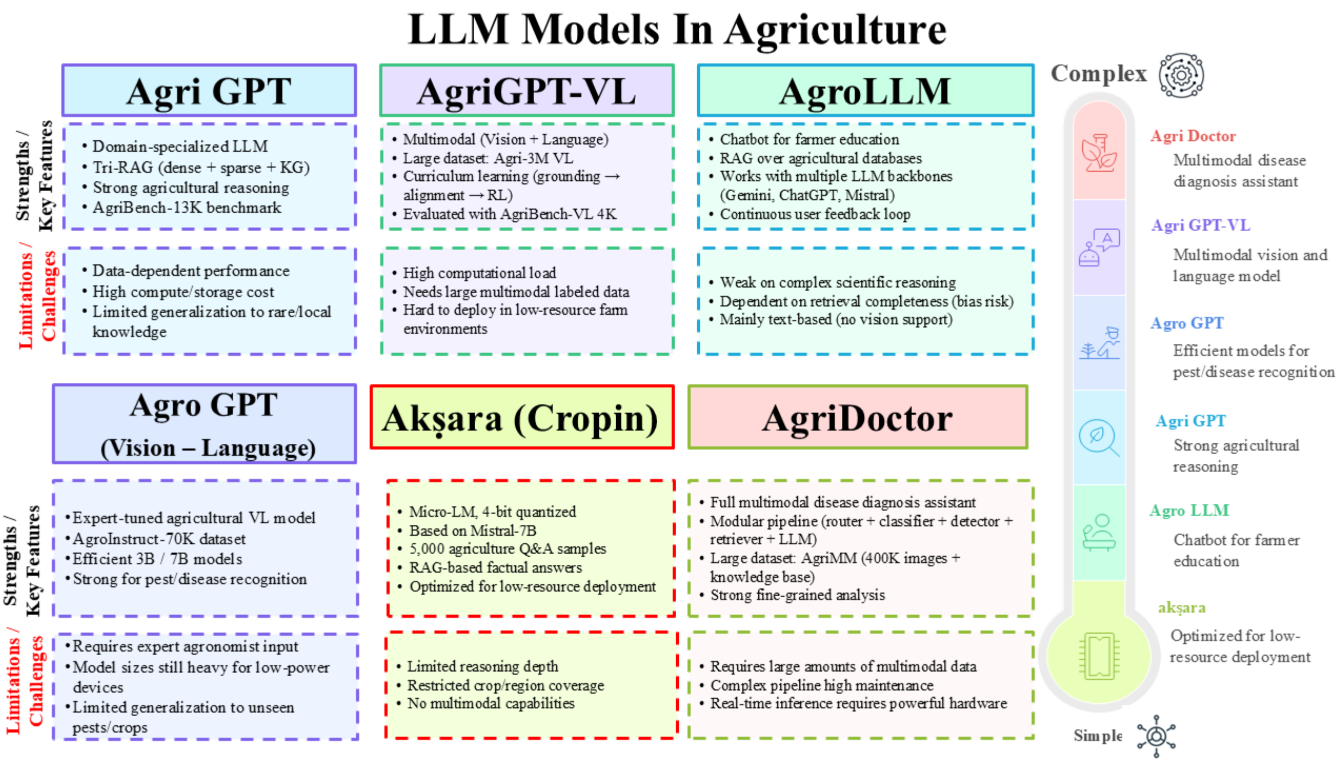

Figure 4. LLM application flow chart for Agriculture technology

proactive unmanned operations, secured by blockchain but also emphasizes the necessity to improve the model reliability, validity and support for real-world adoption of smart solutions [21]. Feng et al. devised a combination of LLMs with Internet of Things (IoT) technology that can significantly enhance smart agriculture by enabling real-time data collection and decision-making for optimized resource management. Using this approach, some key benefits such as precision irrigation, targeted pest management, and improved crop health monitoring with minimal human oversight are obtained. According to the author's claim, the widespread adoption of LLM-IoT systems supported by the government, NGOs, industry, and researchers can boost the efficiency, resilience, and sustainability in the agricultural domain. Eissa (2024) reported that the co-existence of AI and robotics in precision agriculture effectively enhances efficiency, optimize resource use, and increases crop yields, but challenges need to be addressed, such as high costs, technical complexity, and data privacy to enable widespread adoption in far-flung areas [20]. Patel et al. presented a hybrid approach based on GNN and LLM for Crop Field (H-GNNLM-CropField), obtained by integrating Graph Neural Networks (GNNs) and LLMs for real-world crop health prediction and developed an autonomous agricultural management. They tested their approach across 12 farms over 18 months, and achieved 94.2% crop health prediction accuracy, 87.3% pest detection precision, and 23% improvement in resource utilization successfully. Multimodal data from satellites, UAVs, IoT soil sensors, and weather stations are merged to provide actionable insights for precision farming, robust performance under diverse conditions, economic benefits, flexible implementation and high farmer adoption potential [15].

3.2. Current LLM models in agriculture

Considering the use of LLM models in agricultural applications, several specialized models have been proposed, each with unique strengths and limitations, as summarized in Figure 5 and compared in Table 1. AgriGPT is a domain-specific LLM ecosystem that leverages Tri-RAG (dense + sparse + knowledge graph) for reliable reasoning and is evaluated on AgriBench 13K; however, it depends heavily on the quality and coverage of agricultural data and may incur high computational costs [22]. AgriGPT-VL extends this approach to a multimodal vision-language framework, trained on a large agricultural corpus (Agri3M-VL) for image-captioning, VQA, and reinforcement learning tasks, though it is computationally demanding and requires extensive labeled datasets [23]. AgroLLM serves as a chatbot for farmer education, using RAG over open-source databases with flexible backbone LLMs, but it may struggle with technical tasks and vision-based applications [24]. AgroGPT (Vision-Language) specializes in fine-grained recognition of diseases, pests, and plants with expert-tuned datasets, offering high accuracy at the cost of resource-intensive expert input and deployment challenges on low-power devices. Aksara (Cropin) is a lightweight, efficient micro-LM optimized for crop management Q&A, suitable for resource-constrained environments, but limited in reasoning depth and multimodal capabilities [25]. Finally, AgriDoctor is a multimodal assistant for disease diagnosis and knowledge interaction in a farm, excelling in fine-grained domain-specific tasks using extensive annotated datasets, though its

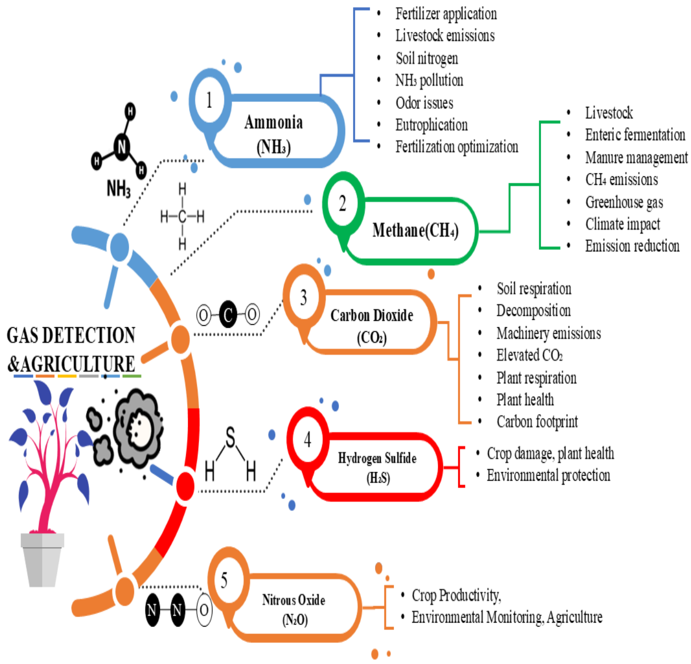

Figure 5. Popular LLM Models in Agriculture technologies (Agritech)

modular architecture and high data requirements pose deployment challenges, particularly in developing countries lacking telecommunication infrastructure. Overall, these models demonstrate the possibility of the replacement of the traditional practices with full automated and predictive farming with the help of LLMs and the opposition to the trade-offs between performance, the financial budget, and the feasibility of the deployment in the perspective of the application [26].

A Comparison of present LLM models applied in the agricultural cyber-physical system illustrates their respective strengths, weaknesses, applicability and practices in significant tasks in the farm. Another example is AgriGPT, a domain-specific LLM whose purpose is to reason about agriculture to perform retrieval-augmented generation (Tri-RAG) and is evaluated on AgriBench 13K. This platform offered some key advantages such as domain grounding; though it requires substantial computational resources and may require verification of a diverse knowledge base to avoid rare or local agricultural knowledge [22]. AgriGPT VL and AgroGPT (Vision-Language) extend these features by incorporating multi-modal capabilities (vision + language), enabling tasks such as crop disease recognition, pest identification, and image-based reasoning. However, they are more resource-intensive and need large, labelled datasets. AgroLLM functions as a chatbot for farmer queries and knowledge dissemination, flexible across different LLM backbones but limited in multimodal or complex predictive tasks in agricultural environments. Aksara (Cropin) is a micro-LLM optimized for efficiency and deployment in resource-constrained settings; while it provides reliable crop management recommendations, it lacks in deep reasoning and machine vision capabilities. AgriDoctor combines multimodal input with a modular pipeline (classifier, detector, knowledge retriever, and LLM), achieving high performance in fine-grained disease diagnosis at the cost of extensive data and deployment infrastructure. Selecting an LLM for agriculture depends on harmonizing computational efficiency, multimodal capabilities, domain-specific knowledge, and the intended practical application, whether it is meant for advisory services, disease monitoring, yield prediction, or autonomous farm operations. Lu et al. demonstrated the application of Artificial General Intelligence (AGI) in agricultural robotics, enhancing task efficiency, human-robot interaction, and real-time decision-making across multiple farm operations, paving the way for fully autonomous precision agriculture [27]. Johnson & Wilson proposed a multi-round prompt engineering approach that leverages LLMs for intelligent agricultural machinery management, demonstrating superior accuracy and actionable recommendations compared to single-prompt and CoT/ThoT methods [28].

While the comparison of existing agricultural LLM models in Table 1 is primarily qualitative, quantitative benchmarking remains an important research gap in current literature. Limited available reports suggest that models such as AgriGPT and hybrid GNN–LLM systems achieve prediction accuracies exceeding 90% in controlled scenarios, while lighter models (e.g., micro-LLMs) offer reduced latency and computational cost at the expense of reasoning depth. However, standardized benchmarks across datasets, evaluation protocols, and deployment scenarios are still lacking. Therefore, future work should focus on establishing unified benchmarking frameworks incorporating performance metrics such as accuracy, inference latency, computational cost, and robustness under varying agricultural conditions.

4. Integrating LLMs and Robotics in Modern Agriculture

The integration of LLMs into agricultural robotic systems enables a transition from reactive automation to proactive and context-aware decision-making. This capability has the potential to significantly enhance adaptive farming practices, particularly in dynamic environments where multiple environmental and operational factors must be considered simultaneously. LLMs enhance robotics by enabling natural language understanding and intuitive human–robot interaction, enabling robots to interpret high-level goals and generate actionable plans. Multimodal LLMs enable robots to process text, images, and sensor data, improving environmental perception by providing contextual knowledge and enabling them to adapt to new tasks without reprogramming. In agriculture 5.0, LLMs support simulation and decision-making to optimize performance and reduce errors in farm management by integration of robots to perform precise manipulation such as planting, harvesting, surveillance and crop monitoring [29]. Robots in agriculture play a critical role in meeting growing food demands in an effective manner by shifting labour-intensive tasks to high-tech machines [30]. Automation reduces human labour costs while working 24/7 without breaks and mitigates trained labour shortages in technologically advanced countries. On top of this, robots facilitate quality improvement and simultaneously improve productivity besides, ensuring sustainable practices in farming [31]. Unmanned Aerial Vehicles (UAVs), also known as drones, are some of the popular categories of robots used in agriculture where they have become an indispensable platform in the contemporary farm [32]. They are mostly utilized for air sampling and monitoring and scouting crops to give an affordable overview to the farmers about crop status, soil, irrigation, and pests. Besides, they may also be configured with some extra payloads in order to carry out more specific operations like spraying fertilizers, pesticides, or herbicides so that the usage of chemicals is reduced as well as the environmental pollution. The UAVs allow a more effective decision-making process and facilitate the practice of precision agriculture because they have proven to be more efficient with the mobility that allows the maximum area to be covered in a short period and reach rugged areas; this leads to an improvement of crop yield and productivity. Albiero estimated the agricultural robotics as a prevailing and essential direction, which is predetermined by the increased demand and the cost reduction in production. Besides, he stated that the present robotic systems are growing to be used in both simple and complex works like sowing, weed 306 control, pest and disease monitoring, pruning, harvesting and even irrigation at the greenhouse through the use of sophisticated sensors and computer vision studies [33]. Paul et al. heighted the importance of the agricultural robots, which are being augmented by the AI, and the new technologies, and are increasingly introduced to perform various tasks, such as harvesting, weed management, seeding, soil diagnostics and environmental control, with the tendencies of their usage growing rapidly due to the development of new technologies and the work done by researchers [34]. According to another research, Qiao et al. mentioned that the networked sensors, along with AI as a brain and robotics actuation, issue plant phenotyping and enable an automated environment that

Table 1. Comparison of Agriculture-focused LLMs and Vision-Language Systems (VLS) [22–26]

Model	Strengths / Key Features	Limitations / Challenges
AgriGPT	Domain-specialized LLM ecosystem for agriculture. Uses Tri-RAG (dense + sparse + knowledge graph) for retrieval-augmented generation, enabling more reliable reasoning. Introduces AgriBench 13K benchmark for evaluating agricultural reasoning performance.	Being domain-specific, its performance depends heavily on the quality and coverage of agricultural data. Training and deployment costs are relatively high. Generalization to local agricultural knowledge remains limited.
AgriGPT-VL	Multimodal (vision + language) model tailored to agriculture. Utilizes the Agri 3M-VL corpus containing image-caption pairs, VQA samples, and reinforcement learning data. Employs curriculum learning including grounding, shallow/deep alignment, and GRPO-based reinforcement learning for enhanced multimodal reasoning. Evaluated using AgriBench-VL 4K and LLM-as-judge methodology.	Computationally intensive because of multimodal processing. Requires large-scale labeled vision-language datasets that are difficult to maintain. Deployment in resource-constrained farming environments may be challenging.
AgroLLM	Chatbot-oriented system for farmer education and agricultural question answering. Uses retrieval-augmented generation over an open-source agricultural database. Compatible with multiple LLM backbones including Gemini 1.5 Flash, ChatGPT-4o Mini, and Mistral-7B. Supports continuous feedback mechanisms for improving answer quality.	May struggle with advanced scientific reasoning and predictive agricultural tasks. Performance depends on the completeness and quality of the retrieval database. Primarily text-based and lacks native vision capabilities.
AgroGPT (Vision-Language)	Trained on the 70K-sample AgroInstruct dataset. Available in efficient 3B and 7B parameter variants. Designed for agricultural recognition tasks such as pest and disease identification. Evaluated using the AgroEvals benchmark.	Requires expert agronomist involvement for dataset construction and validation. Even reduced-size models may remain unsuitable for low-power devices. Generalization to unseen crops and pests can be limited.
Aksara (Cropin)	Lightweight micro-language model derived from Mistral-7B and quantized to 4-bit precision. Trained on approximately 5,000 agriculture-related question-answer pairs. Uses RAG mechanisms to improve factual grounding and is suitable for resource-constrained deployments.	Limited reasoning capability compared to larger models. Coverage is restricted to the training dataset and target regions. Does not provide strong multimodal functionality.
AgriDoctor	Multimodal agricultural assistant supporting disease diagnosis and advisory services. Uses a modular architecture consisting of a router, classifier, detector, knowledge retriever, and LLM. Built on the AgriMM dataset containing 400K disease images, 831 knowledge entries, and 300K bilingual prompts. Demonstrates strong performance in fine-grained agricultural analysis.	Requires large-scale multimodal datasets and complex system maintenance. Real-time deployment demands significant computational resources, which may not be available in many farming environments.

facilitates stress detection and a data-driven decision support system, which helps to reduce the usage of pesticides and speed up sustainable farming activities [35]. According to Fountas et al., vision-based perception is instrumental in agricultural robotics, and it allows carrying out tasks such as weed identification, crop exploration, pathology recognition and identification, navigation, crop harvesting and spraying. It is worth noting that the RGB cameras are cheaper and most popular vision sensors, whereas AI algorithms deliver a positive outcome in various applications [36]. Angamgari introduced a novel UAV system that has an integrative assembly of LLMs and a safe voice-command interface, object recognition by YOLOv8 and a task-scheduling dynamic algorithm that which was tested in a simulated farm setting. The outcomes revealed a better command management, accurate crop inspection, reduced operator involvement, and efficient performance under challenging conditions such as wind and fog. These performance indicators support the fact that it is efficient and can be used in situations of modern precision farming environments [37]. Likewise, according to Onteddu et al., robotics and AI-driven autonomous agriculture can improve productivity in agriculture through water, fertilizer, and pesticides optimization. It implies the automation of labour-intensive work, as well as data-driven decision-making for farm managers. Performance barriers include high initial costs, technological complexity, and data management concerns that may hinder adoption, underscoring the need for further research on intelligent mobile robots powered by AI algorithms, and data integration strategies to enable equitable and scalable edge-deployment in real-world farming scenarios [38]. Using LLMs based agricultural robots can enable intelligent decision-making based on sensor data, weather, and crop conditions to help diagnose plant health issues, suggest interventions, and optimize farming tasks using natural language processing, to instruct and monitor robots. Based on historical data, LLMs allow robots to learn from past operations and adapt to changing field conditions for improved efficiency [39]. Bechar & Vigneault, 2016 and Fountas et al., 2020, proposed AI-guided robots that can precisely remove weeds and minimize herbicide use, while sensor-equipped harvesting robots optimize fruit picking and lower labor costs. Similarly, drones equipped with imaging sensors monitor fields for pests or plant pathologies for an early intervention. The design and development of AgriRobots require multidisciplinary expertise in robotics, AI, plant science, and data analytics, to address the complexity of real-time acquisition and processing of large-scale agricultural data [40, 41]. Li et al. remarked that the application-specific agricultural robots, such as AI-guided weeding robots, sensor-equipped harvesting robots, and drones for crop monitoring, can automate labor-intensive tasks, significantly reduce herbicide use, optimize harvesting efficiency, and enable early disease or pest detection for timely control. They also highlighted that integrating foundation models (FMs) with these robots can augment predictive capabilities, enabling precision control, and enhancing overall operational efficiency in smart agriculture applications [42]. Zuzuarregui et al. presented a natural language robotic mission planner that allows non-specialist supervisors to control multiple agricultural robots via a single interface. As a result, complex mission planning task is simplified for multi-robot coordination and human-robot collaboration [43].

4.1. LLM in Agriculture for Integrating Gas Detection Mission

Although diverse tasks exist in the agricultural domain, pollutant and greenhouse gas (GHG) detection is one of the most important applications because of its direct impact on product quality and environmental sustainability, as shown in Figure 6. The production of carbon dioxide (CO_2), methane (CH_4), ammonia (NH_3), ethylene (C_2H_4), and nitrogen oxides (NO_x) from soil activities and fertilizer use significantly influences crop health, soil processes, and livestock well-being, thereby affecting overall agricultural productivity [31, 32, 44]. Deep learning has emerged as a transformative approach for real-time gas detection in agriculture, enabling robotic systems to interpret complex sensor data with high accuracy and greater adaptability than traditional threshold-based techniques. Furthermore, deep learning algorithms can automatically learn intricate relationships between sensor signals, threshold values, and gas concentrations, making them highly suitable for noisy and dynamic agricultural environments, including both indoor and outdoor conditions [45].

The collected sensor data undergoes several preprocessing stages, including noise reduction, normalization, re-sampling, and drift compensation, to ensure consistency across varying environmental conditions before further analysis. Feature extraction may involve engineered features such as signal derivatives and frequency-domain characteristics, as well as automated feature learning through convolutional neural networks (CNNs), which can directly capture spatial and temporal representations from raw sensor signals [46]. Table 2 provides a summary of the important Major Gases, their importance for detection, and their impacts on agriculture. The optimal management of photosynthesis, plant growth and greenhouses depends on the monitoring of carbon dioxide (CO_2) levels. Methane (CH_4) and ammonia (NH_3), which are typically produced by farm animals and by the application of fertilizers, are symptoms in particular of nutrient imbalance, environmental pollution, and inefficient farming practices. Ethylene

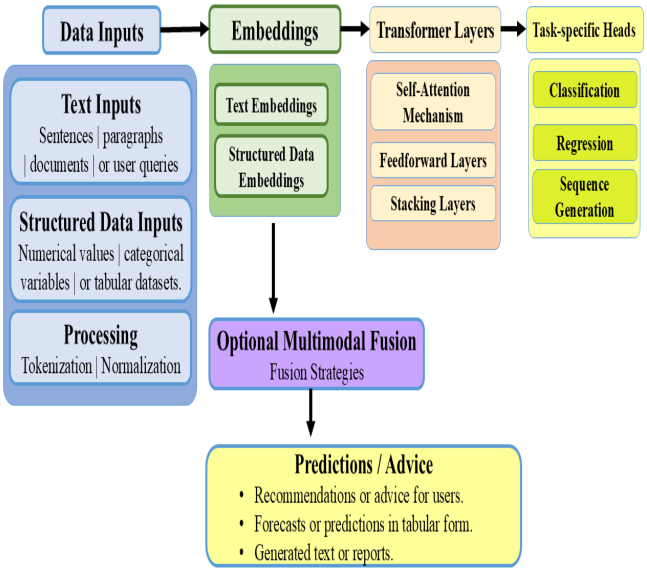

Figure 6. Environmental Gas detection in Smart Agriculture via LLM

(C_2H_4) acts as a plant hormone in important processes such fruit ripening, senescence and stress reactions [47].

Excessive NH_3 is a very great danger to agriculture systems. It can result in soil accidification and imbalance in soil nutrients, impacting the growth and productivity of crops, due to high levels of NH_3 in the soil and atmosphere. High levels of ammonia can also cause injury to leaf tissues, and decrease photosynthetic rates, and can contribute to the production of secondary products that can cause excessive stress to crops. Hence, ensuring proper management of NH_3 emissions via continuous monitoring and its effective c ontrol is vital for soil health, crop protection, and agricultural production sustainability [32]. Having access to ongoing surveillance of agricultural environmental data allows farmers to make timely decisions at the right time that ensure optimal growth conditions, higher yields, lower environmental impacts, environmental law compliance, and lower greenhouse gas emissions, which enable sustainable operations in agriculture [48].

To sense the hazardous environmental gases at farm, several sensor technologies are applied in agricultural contexts, each with unique detection principles, strengths, and limitations. For example, Metal Oxide Semiconductor (MOS) sensors are widely used due to their low cost and relatively simple operation, as they detect gases by measuring changes in the resistance of a heated semiconductor surface upon interaction with target molecules. However, due to their high sensitivity, MOS sensors are often affected b y environmental factors such as humidity and temperature, leading to sensor drift over time, requiring frequent calibration for accurate operation.

Furthermore, proper installation to reduce dust and VOC interference in farm environments is also needed [49]. Electrochemical sensors are selectively to detect toxic gases like NH_3 and CO by generating electrical current proportional to concentration of target gas because of electrochemical oxidation or reduction of gas at the surface of electrode. These sensors not only take up little space and are low consuming, but also relatively stable and can hence be used in livestock barns or in closed greenhouses. Yet, limited life, inherent sensitivity to temperature changes, and the need for frequent replacement will continue to represent important limitations and a challenge for technical experts to diagnose and trouble shoot the sensor installations [50]. Because of their use of infrared absorption features at specific wavelengths of greenhouse gases, Non-Dispersive InfraRed (NDIR) sensors are commonly used in the monitoring of greenhouse gases like CO_2 and CH_4. NDIR sensors are not sensitive to cross sensitivity from other gases to a great extent, are highly accurate, and have long-term stability. Although beneficial, these have drawbacks, such as they being more expensive and requiring regular cleaning to maintain optical precision appropriate for precision agriculture use [51]. The PIDs have been proven to detect so-called volatile organic compounds (VOCs) and some gases that are useful to monitor plant stress and soil monitoring, by applying UV-light that ionizes the compounds or gases present in the air and measuring and quantifying the created current that is proportional to the amount of the gases. The drawback of PID's is that they can be highly sensitive and may be prone to false positives if not calibrated with desired gases and thus may not be used for large scale farms. Additionally, sensor placement strategies are also important to consider in automated farms due to their peculiar needs [31, 52]. For instance, CO2 sensors in the greenhouse need to be placed close to the plant canopies to measure the respiration and photosynthesis properly while NH3 sensors should be placed at the height of the animal's head to understand the exposure to the animal. Likewise, methane sensors in paddy fields or compost facilities must account for ground-level emissions and dynamic airflow. Therefore, maintenance schedules for calibration, sensor drift compensation and the fusion of multiple sensor types is critical for ensuring reliable operation under changing environmental conditions [53].

In their study, Senyk et al., 2025 evaluated the optimization of AI in predicting the sequestration in agricultural crops, by surveying the physical and environmental attributes of crops, including temperature, humidity and insolation using physical and Earth-based sensors, GIS and satellite data collection. Authors used correlation analysis and regression analysis; they

Table 2. Main gases, their reasons for detection, and associated effects

Gas	Strengths/Key Features	Limitations / Challenges
Ammonia (NH_3)	Indicates fertilizer application, livestock emissions, and soil nitrogen levels.	High NH_3 causes air pollution, odor problems, and contributes to eutrophication; monitoring helps optimize fertilization.
Methane (CH_4)	Produced by livestock (enteric fermentation) and manure management.	CH_4 is a potent greenhouse gas; monitoring helps reduce emissions and climate impact.
Nitrous Oxide (N_2O)	Released from fertilized soils and manure decomposition.	N_2O is a strong greenhouse gas and depletes ozone; monitoring helps manage fertilizer efficiency.
Carbon Dioxide (CO_2)	Emissions from soil respiration, decomposition, and machinery.	Elevated levels indicate soil and plant respiration rates; monitoring helps assess plant health and carbon footprint.
Hydrogen Sulfide (H_2S)	Produced in manure storage and anaerobic soil conditions.	Toxic to humans and animals; monitoring ensures safety and prevents crop damage.
Ozone (O_3)	Secondary pollutant affecting crops.	High O_3 levels reduce crop yields and quality; monitoring helps protect sensitive crops.

used predictive models to determine the CO_2 sequestration potential depending on crop yields and the area under sowing. The XGBoost gradient boosting algorithm was utilized to adequately explain the variability between years as well as enhance the predictive performance. This methodology indicated that productivity of field crops can be used to reduce the concentration of atmospheric CO_2 significantly, and the AI-independent methodology offers a healthy model of planning and carbon farming in sustainable agriculture. Transfer learning and super-simulated deep networks have been used in resource-constrained applications to ensure that the computation overhead is minimized and the capability is still accurate [54]. Despite promising results, deploying deep learning models in real-world agricultural farms is still challenging due to the environmental variability, such as fluctuating humidity, dust, and sudden temperature shifts, that can introduce noise in models trained under controlled conditions. Furthermore, sensor drift and degradation over time further complicate the performance consistency, requiring an adaptive recalibration and retraining framework to update the model parameters. Integration of Agritech Apps into mobile robotic platforms are hindered due to constrained processing power and battery life. Edge AI approaches are helpful as they use models which are optimized for real-time inference directly on robots or IoT nodes. Thus, edge AI algorithms are seen as a solution to reduce latency and reliance on cloud infrastructure [55]. Considering the overwhelming use of LLMs, edge-AI models can analyze large sensor and satellite datasets related to agricultural data such as gas emissions. Therefore, the communication requirements are lesser as only the edge-computed results are transmitted to the actuators to enhance farm efficiency and promote sustainability [56]. One example of deployed actuator network may consist of various farm robots to carry out necessary tasks by replacing human workers, who have limited capability to monitor sensor data and take necessary actions.

4.2. Data Fusion Approaches Enhanced by LLMs in Precision Farming

In agriculture 5.0, data fusion integrates information from multiple sources such to provide a comprehensive view of farm conditions; LLMs further enhance this process by analyzing complex, multi-source datasets, identifying patterns, and generating actionable insights as shown in Figure 8. Data fusion techniques in agricultural domain can be categorized as follows: Early (data-level) fusion merges raw data from sensors, UAVs, and satellites before processing. Feature-level fusion extracts and combines features from each source for modeling. Decision-level (late) fusion processes each dataset independently and integrates the outputs, while hybrid fusion combines multiple strategies to enforce the strengths of each approach. Key challenges in agricultural data fusion include handling heterogeneous data formats, ensuring data quality and completeness, aligning temporal and spatial information, managing computational complexity, maintaining scalability, and ensuring interpretability. Recently, early fusion is preferred for tightly coupled sensor systems but constrained due to heterogeneous sources; feature-level fusion is widely used for UAVs and satellite imagery; decision-level fusion suits independent or asynchronous datasets; while hybrid fusion is emerging as a robust approach for crop health monitoring, yield estimation, and pest detection [15, 16, 57]. Figure 8 shows swarm robots powered by multimodal sensors and edge AI enhanced by LLM decision-support systems.

As shown in Table 3, data fusion in agriculture integrates information from multiple sources using different methods, each with distinct strengths and challenges. Early fusion merges raw data before processing, effective for tightly coupled sensors but limited with heterogeneous sources. Feature-level fusion combines extracted features, widely used for UAV and satellite imagery, supporting crop monitoring and yield prediction. Decision-level fusion integrates outputs from independently processed datasets, suitable for pest and disease detection. Hybrid fusion combines multiple strategies for robust crop health prediction and resource optimization, though it is computationally intensive and complex to implement. With the aim of data fusion Zaidner & Shapiro, 2016 proposed a novel data fusion algorithm called Multi-Sensor Probabilistic Integration (MSPI) for low-cost localization and navigation of autonomous vineyard sprayer robots. The study aimed to overcome challenges such as limited manpower and exposure to pesticides by enabling precise autonomous navigation. Their approach combined data from multiple sensors (DGPS, IMU, visual, and wheel odometry) using a likelihood ratio test (LRT) for optimal state estimation. The robot's kinematic model was validated through simulation and field video data, showing that low-cost sensors can achieve reliable accuracy when appropriately filtered and fused. The MSPI algorithm outperformed traditional EKF methods, offering a feasible, analytically grounded alternative to fuzzy logic approaches for vineyard robots, though real-time implementation and robustness under high sensor discrepancies remain areas for future work [58].

Ahmed et al., 2022 reviewed the technology and data fusion methods to enhance site-specific crop monitoring by combining multiple sensor types, such as optical, thermal-infrared, multi and hyper spectral, LiDAR, to improve the monitoring of key crop parameters like nitrogen content, chlorophyll, leaf area index (LAI), and aboveground biomass (AGB). The study emphasized the integration of data from ground-based platforms (tractors, robots), aerial (UAVs), and space-borne sensors (satellites) for precision agriculture. By combining airborne and terrestrial LiDAR data, more accurate and site-specific crop information is obtained despite some practical limitations arising from sensor multimodality, noise, and resolution. They suggested that future development of autonomous agriculture could further optimize data fusion applications for efficient crop monitoring and improved farm management [59]. Barbedo in argued about the complexity of Agro-ecosystem due to which single-sensor data is often ambiguous, and data fusion from multiple sources is necessary to extract reliable information, though adoption barriers still remain [60]. Barrile et al. demonstrated the integration of satellite, UAV, and autonomous tractor data using fusion and GIS for optimized vineyard management in Agriculture 4.0 [61]. Katharria et al., 2025 conducted a comprehensive survey on machine learning (ML) applications in smart agriculture, by analyzing over 70 studies, covering pre-harvesting, harvesting, and post-harvesting phases. They also discussed the potential of machine learning combined with remote sensing, IoT, and climate data to improve predictive accuracy and decision-making. They also reviewed some real-world case studies of AI-driven agricultural enterprises such as Kisan GPT, Jiva, CropIn, and Blue River Technology, illustrating practical implementations of fusion-based machine learning models. Moreover, the authors also presented bibliometric analysis by summarizing available public datasets for model training, and discussed methodologies e.g., ensemble learning, Bayesian inference, and deep learning-based feature fusion for handling heterogeneous agricultural data [62]. Satellite imagery plays a vital role in modern agriculture by providing large-scale, multi-spectral information to support crop monitoring, yield estimation, soil and moisture analysis, pest and disease detection, and land-use mapping. Vegetation indices such as Normalized Difference Vegetation Index (NDVI) derived from images enable early detection of crop stress and health issues, while temporal analysis helps predict yield and assess the effects of environmental factors. By combining the satellite data with the UAV images, with IoT soil sensors and weather data based on fusion of data, experiences the accuracy of the predictions can be improved, and the data can be transformed into meaningful actions, like detailed irrigation plans or recommended pest management. Nonetheless, it has its strengths accompanied by the problems of spatial and temporal resolution, interference with the cloud cover, computational needs, and the ability to align satellite data and ground measurements. Overall, satellite data will be an effective tool to get a holistic picture of what is happening in the farm, enabling judgment-based farming and decision-making in real-time [16, 57]. In agriculture 5.0, gas sensor-based UAVs measure emissions such as ammonia and methane on soil, fertilizers, and livestock and the fusion of gas sensor measurements with GPS, temperature, humidity and wind data can be used to more accurately measure gases on a field and hotspots can be identified on the fields to intervene. Temporal data fusion

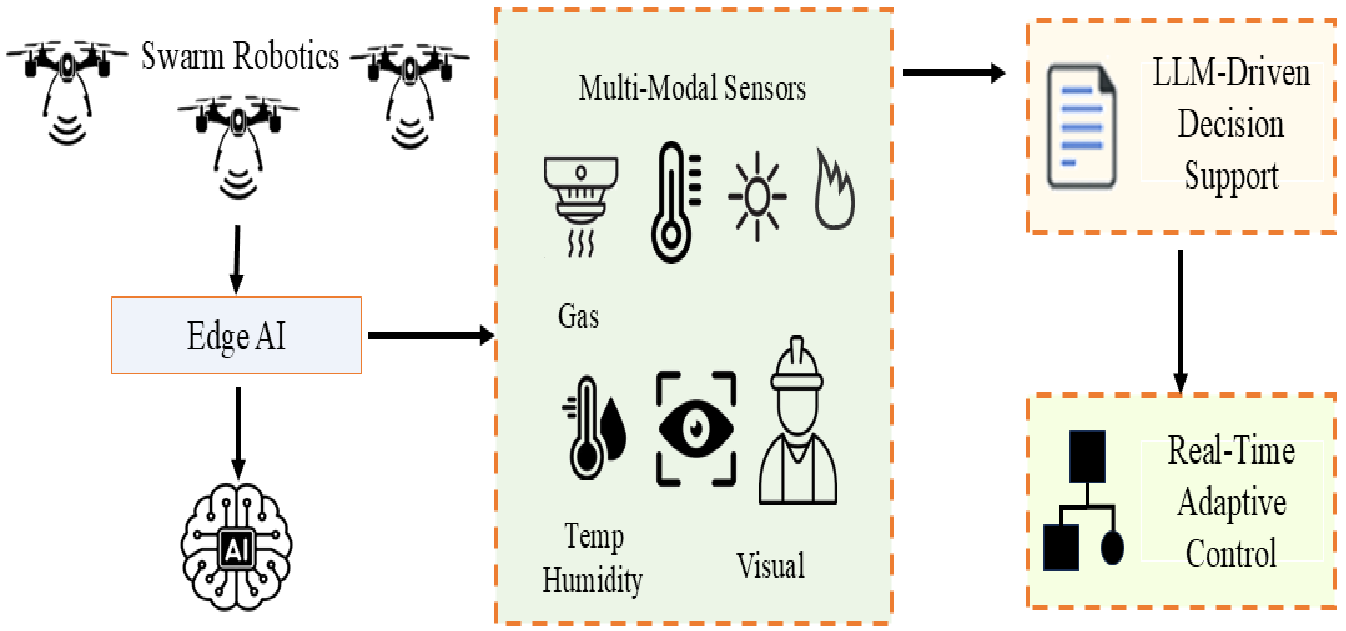

Figure 7. UAVs detection enhanced via LLM-driven decision support

Table 3. Data fusion in agriculture

Data Fusion Method	Description	Challenges	Current Status of Development
Early (Data-Level) Fusion	Combines raw data from multiple sources before processing	Difficult with heterogeneous data; sensitive to noise; requires temporal/spatial alignment	Effective for tightly coupled sensor systems; less suitable for heterogeneous sources
Feature-Level Fusion	Extracts features from each data source and merges them for modeling	High computational requirements; needs feature normalization; interpretability issues	Widely used for UAV and satellite imagery integration; robust for crop monitoring and yield prediction
Decision-Level (Late) Fusion	Processes each data source independently and combines the decisions or predictions	Loss of detailed information; dependent on quality of individual models	Preferred when datasets are independent or asynchronously collected; widely applied in pest detection and disease monitoring
Hybrid Fusion	Combines multiple fusion strategies (data-level + decision-level)	Complex design; computationally intensive; requires careful tuning	Emerging in precision agriculture for robust crop health prediction and resource optimization; shows improved performance

monitors the trend of emissions allowing the farm to be managed more efficiently with the support of integrated LLMs. Fused data assists the UAV navigation and proposes mitigation measures to achieve clear, effective, and sustainable farming [9, 32].

5. Case Studies and Applications in the Farm

There are various case studies of the practical implementation of robotics and sensor-based gas monitoring in agriculture involving a variety of settings: greenhouses, livestock farms, and open fields which demonstrate how robotic troops, in combination with AI and LLMs, are changing the process of tracking and controlling agricultural bi-products. In greenhouses, sensing and robotic technologies are usually applied in order to keep in check the delicate balance of the gases that directly affect crop health and productivity [31]. As an example, gas sensors on mobile robots can constantly observe the areas of carbon dioxide, ammonia, and methane, whereas avoiding obstacles and immediately, such data is transformed with the help of AI-based fusion algorithms, which helps the robot differentiate between natural changes and hazardous gas concentrations at the exact sites to signal about an abnormality [32]. Additional features of the LLM's application include assistance for farmers with a simple definition and solutions, e.g., the ventilation systems should be improved or the timing of fertilization modified in different places [65]. These examples demonstrate how robotics in controlled environments not only detect gases but also support decision-making in an easy way for non-technical managers. Likewise, in livestock farming, robotic gas-monitoring systems have been introduced to improve both animal welfare and farm management efficiently [66]. For example, ammonia emissions from manure can accumulate quickly in enclosed barns and cause health issues for animals and workers in a similar manner. To address this issue, mobile robots equipped with infrared or electrochemical sensors integrated with AI-driven data fusion are deployed to patrol barns and detect elevated gas concentrations and generate LLM-based advisories and warnings to farmers to control the desired emission trend, identify recurring hotspots, and adopt targeted interventions such as improved cleaning routines or adjustments to ventilation. By automating detection and reporting, these systems relieve labor demands and support compliance with national and international environmental standards [67]. In open-field agriculture, the deployment of robotic gas monitoring is more challenging due to the variability of natural conditions, therefore, both unmanned ground vehicles and drones are deployed to monitor GHGs released from each cell composed of either farms or livestock producing decomposed organic matter [68]. These robots frequently include gas-detection, along with visual imaging and weather sensors, to provide multi-layered insight into field conditions and, as a result, allow the system to remove interference from wind, rainfall, or sunlight, which might otherwise affect precision [69]. AI aids in the adaptive way of navigation, enabling robots to visit regions with increased emission levels, whereas LLM help to interpret raw data into comprehensible and practical information that a farmer may need to take specific measures, e.g., adjusting the level of fertilizers applied to fields or altering irrigation patterns. The case studies also indicate how the robotics-based gas monitoring systems can be adapted to fit in a variety of agricultural environments even though the technical complexity of the environment of each application varies, the basic structure of integrating robotics with AI, multi-sensor fusion, and language model interpretation is applicable to all these applications [70]. These are examples of how these systems can become operational in addition to the fact that there is a growing trend towards assisting sustainable agricultural practices to mitigate the environmental impacts as well as enabling farmers to make informed and data-driven decisions with the help of technology.

6. Challenges and Limitations

However, in spite of the role played by robotics and AI-based integration in transforming the process of agricultural gas monitoring, such systems are Lego to several issues that include the technical, computational and socio-economic fields. As a general remark, sensor resilience, energy efficiency, AI-scalability, and a cut back on the cost of deployment are initial measures that the technology may undergo before being made exhaustively commercially viable as a fundamental agricultural service [71]. The other important technical problem is linked to sensor degradation. Gas sensors called electrochemical and metal-oxide sensors that use drifting limits, ageing, and capacitance with constant disturbances as found in an agricultural field i.e., heat and dust thus such sensors may have to be regularly recalibrated or changed [72]. Another problem is environmental interference since the sensor readings may be distorted due to such factors as wind effects, rainfall, and changing soil conditions, which constrain the reliability of gas concentration sensing in the open field environment [73]. Additionally, there exists a major restriction in terms of power and mobility when the Robotic platform is used in vast and uneven farm surfaces over prolonged periods, which will be subject to battery drainage in case of a lack of solar-powered backup. Mobility in rough terrain, muddy areas, gradients, and the repose of crops is also another challenge within the fields that further limits the working scope of the mobile platform. Although the solar charging mechanism and lightweight designs provide partial solutions, energy efficiency is still a challenge to the deployment of an autonomous deployment in real-life situations [74]. From a computational perspective, the problems of over-fitting, model generalization, and real-time inference about the full high-resolution samples are in place in AI and LLM models. Data of agricultural gases are very dynamic with respect to the day time, location, type of crops, as well as climate, and thus it becomes hard to learn common robust models that apply to all cases [75]. This means the tiresome attempt to optimize

AI model to one environment that might fail in another one that casts some doubt about scalability. LLMs also offer effective reasoning and decision support, although their applicability in the real-time is limited by the large computational requirements and latency. Their deployment on edge devices is especially difficult as memory and processing power are limited and requires these approaches to be lightweight. However, precise model compression methods require compression techniques that are lightweight but accurate at the same time [76]. Questions of regulations and costs are also important issues, as the Agribots would need to be in line with, say, safety regulations, communication bandwidth and structures vary between the countries [77]. The process to get approvals to deploy globally can be cumbersome and involve extensive bureaucratic procedures and formalities. Furthermore, the recent surge in the price of the Agritech that can be used with the robot combined with the installation of the sensor array and integration with AI suggests that it may not be appropriate for small-scale farmers who constitute a majority of food producers [78]. So, without provision of government subsidies, cooperative ownership and rental services, the progress of widespread adoption could be restricted to large-scale industrial stakeholders [79]. While LLM-integrated robotic systems hold the promise of cutting-edge technology, there are several practical challenges that obstruct the seamless application of these systems in real-world scenarios. They involve high initial cost of the robotic platforms and sensing device, frequent sensor calibration because of the sensor drift, and lack of long-term validation in a variety of field conditions. In addition, soil, climatic and crop type variations render it hard to adaptively generalize models without retraining. The key challenges in implementing robotics for agricultural gas monitoring using sensor fusion and by AI are presented in Table 4. It is noticed that the categories are grouped into technical, computational and socio-economic/regulatory categories as discussed above. There are technical problems, which are primarily related to power and mobility issues, sensor degradation and the influence of the environment [80]. Smart-edge models and real-time constraints [81] cause problems in computational requirements. Increase in socio-economic and regulatory issues because of the increased cost to a robotic platform and technology, and strict safety and environmental regulations are required [32]. All these multi-layered aspects should be considered to support wide and secure scaling and deployment of intelligent agricultural monitoring systems in the scope of Agriculture 5.0 as described in [82]. One of the major obstacles to the implementation of AI systems in farming is the lack of the "generality" of the AI amongst different conditions. This is directly related to the scalability and robustness of LLM integrated robotic systems. To overcome this limitation, domain adaptation techniques, transfer learning and use of multiple and large-scale datasets with diverse agricultural conditions would be the area of interest in the future. Moreover, adaptive systems with the ability to learn continuously and automatically to recalibrate as the environment provides feedback can be a powerful addition to achieving operational flexibility and potential in the real world.

7. Future Directions

On the one hand, the future of robotic agricultural solutions will take over the world trend due to the smooth implementation of new technologies like edge AI, swarm robotics, Internet of Things (IoT), and advanced LLMs. As high processing power can fit into a small area, Edge AI can be used to process data in real-time and on the robotic platform, minimizing lag time and enhancing responsiveness. Alternatively, swarm robotics enables adaptable, dependable and scalable surveillance in large farms, thereby making them accessible. The IoT-based connectivity will guarantee constant data collection by the scattered sensors. Given the available computational resources, adaptive decision-making, and modern LLM, more intricate multi-source datasets can be processed to deliver predictive insights and automatic recommendations and contribute to streamlining farm productivity. Gas detection multi-modal sensing with considerations to environmental conditions and visual images provides a holistic view of the situation and allows anticipatory maintenance of the robotic platforms as well as the agricultural equipment to prevent interruptions and guarantee the stable functioning. Also, adaptive robust control systems, which operate via AI and multi-sensor fusion, can automatically adjust the operations, including ventilation, temperature and humidity control, irrigation, or chemical dispensation depending on gas levels, crop health, and external weather conditions. There are many opportunities in future research where the development of nonlinear and robust algorithms for multi-modal data fusion can be done. The cost of such algorithmic complexity is finding better swarm organization to autonomous decision-making tasks, and combining the dynamic risk evaluation of Agritech with predictive analytics based on the LLM. These developments are likely to enable the future generation of robotic systems to work with little human control, as well as to deliver optimal agricultural productivity, crop safety and environmental sustainability.

8. Conclusion

This paper defines the revolutionary opportunities of robotics, artificial intelligence, and language models,

Table 4. AI implementation challenges and mitigation strategies

Category	Challenges	Description
Technical	Sensor degradation	Drift, aging, and reduced sensitivity of electrochemical and metal-oxide sensors due to temperature and humidity.
	Environmental interference	Wind, rainfall, and fluctuating soil conditions distort sensor readings.
	Power and mobility constraints	Limited battery life; difficulty navigating mud, slopes, uneven terrain, and dense crops.
	Model generalization and over-fitting	AI/LLMs trained in one environment may perform poorly in different regions, crops, or climates.
	Real-time inference constraints	High computational demands and latency make edge deployment challenging.
Computational	Lightweight model requirements	Need for efficient model compression for accurate deployment on limited hardware.
	High deployment cost	Expensive robotic platforms, sensors, and AI systems limit adoption by smallholder farmers.
	Regulatory barriers	Compliance with safety standards, wireless protocols, and environmental monitoring regulations varies by region.
Socio-Economic & Regulatory	Adoption limitations	Without subsidies, cooperative ownership, or rental models, adoption may remain restricted to large-scale farms.

and the fusion of multi-sensor data to improve sampling and gas identification in farm settings. The real-time scrutiny of harmful gases is possible through the incorporation of autonomous robots with embedded sensors and AI-powered data collection. Therefore, enabling quick identification and remedies of the risks involved compared to the traditional methods. This review explains how LLMs will enable farmers to provide context-sensitive reasoning and predictive abilities to robots to establish an agricultural decision-making paradigm shift. In addition to augmenting this automation by analyzing intricate datasets, offering actionable insights thereof, LLMs promote predictive decision-making as well. These technologies used jointly serve to enhance situational awareness, maximum resource utilization, and operational effectiveness of agricultural process. The critical findings encompass numerous case studies in which sensor-controlled autonomous platforms are coupled with artificially intelligent and powerful data fusion techniques to measure accurately the environmental conditions at the canopy and soil levels of crops, enhancing the safety and minimizing exposure to dangerous materials that trigger specific interventions and thereby reduce the level of stress on the crops and maximize fertilization, irrigation, and pesticide application. Furthermore, the implementation of LLM-based AI frameworks also supports sustainable precision agriculture, as these systems can help increase crop yields and mitigate environmental impacts. In terms of originality, this paper integrates the new ideas-LLM-based robotics, multimodal sensor fusion and adaptive control in a unified approach on climate-smart agriculture to consider the global issues of food security and supply-chains on the one hand, GHG control and mitigation, resource saving and food security on the other. This rigor is reflected in the systematic synthesis of the up-to-date technologies and proven instances. Such integrated systems in real-life applications can be scaled to meet the requirements of smart farming, ensuring safer, more effective, and environmentally friendly operation as well as tackling contemporary problems in agriculture and global warming. Further studies would focus on developing more robust multimodal data compilation for better supervision, advanced swarm robotics to provide scalable, autonomous functionality, and autonomous Agentic AI that relies on Large Action Models (LAMs) to provide real-time decision and actuation assistance. By developing energy-efficient, durable platforms and more affordable implementation strategies, small-scale farmers will be enabled to adopt innovative energy-saving ideas to promote sustainable agriculture.

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