

Advancements in artificial intelligence, particularly in LLMs, have opened up new possibilities for a wide range of industries, including agriculture. One of the most exciting developments is the potential of **function calling** in LLMs, which, when combined with real-time data from satellite imagery and other sensors, can significantly enhance agricultural decision-making. Below, I outline the envisioned workflow and the key challenges that must be addressed for this vision to become a reality.

Function calling in large language models (LLMs) offers tremendous potential to transform agricultural decision-making, especially when combined with real-time data from satellite imagery and other sensors. By acting as the core of a decision-making system, LLMs equipped with function-calling capabilities can access external APIs to retrieve real-time information on weather conditions, soil moisture, and vegetation indices

like NDVI. This system allows farmers and agricultural experts to ask natural language questions like, "Should I irrigate my field today?" or "What is the expected yield of my crops?"

The LLM, using its function-calling feature, can retrieve relevant data from satellite imagery, local weather forecasts, and historical yield records. It then analyzes this information to provide actionable insights. For example, the model might recommend immediate irrigation based on current soil moisture levels and weather forecasts, or suggest additional fertilizer application in two weeks to improve the crop's yield potential. The power of this system lies in its ability to turn complex data into simple, practical recommendations, making advanced agricultural insights accessible to anyone, regardless of technical expertise.

However, there are significant challenges to overcome. Data accuracy is crucial, as decisions must be based on reliable, real-time information. Ensuring that APIs deliver consistent and validated data is essential, as is minimizing latency to allow timely decision-making. Predictive models, too, need to generalize across diverse regions and conditions, which requires extensive training on varied datasets. Farmers must also trust the system, so providing clear explanations for each recommendation is key to fostering confidence in AI-driven decision-making.

Integrating data from various sources — such as satellite imagery, soil sensors, and farm management software — into a unified system requires robust infrastructure. This integration must also account for cost, as accessing and processing real-time data can be expensive. Additionally, privacy and security are critical, as sensitive agricultural data must be protected from unauthorized access.

Despite all these perceived hurdles, the potential benefits are enormous. Farmers can make data-driven decisions, improve resource management, and proactively address issues before they impact yield. Function calling in LLMs could revolutionize agriculture by providing smarter, more efficient ways to manage crops, making real-time data a cornerstone of modern farming.

A Sample Set of Components for an Agricultural Al Workflow

1. Real-time Data Acquisition

Agricultural decision-making starts with data. Satellites and on-the-ground sensors constantly collect real-time data on weather conditions, soil moisture, vegetation indices (e.g., NDVI), and crop health. This data, processed and made accessible through APIs, provides the foundation for actionable insights.

2. LLM with Function Calling

The LLM serves as the decision-making engine, equipped with function-calling capabilities to interact with external APIs. These APIs provide the LLM with access to real-time and historical agricultural data, which is essential for accurate decision-making.

3. User Interaction

A farmer or agricultural expert can interact with the LLM using simple natural language prompts. For instance, they might ask, "What's the current status of my wheat field?" or "Should I irrigate today, and if so, how much?"

4. Contextual Data Retrieval

Upon receiving the query, the LLM identifies the relevant external functions to call. It might request satellite imagery data to evaluate the field's health

via NDVI, retrieve local weather data, and access historical yield data to make predictions.

5. Analysis and Prediction

Once the data is retrieved, the LLM performs an analysis. This could involve statistical models or advanced machine learning techniques to generate crop yield predictions, irrigation recommendations, or pest control alerts based on the data.

6. Actionable Recommendations

Finally, the LLM provides actionable recommendations to the user in natural language. For example:

"Your wheat field is showing signs of water stress. Based on the current weather forecast and soil moisture levels, it's recommended that you irrigate today. Additionally, applying nitrogen in two weeks could boost your predicted yield of 8 tons/hectare."

Benefits of AI Applied to Agriculture

- Data-Driven Decisions: Farmers can make more informed decisions based on real-time data and advanced analysis, resulting in optimized resource management and improved crop productivity.
- Accessibility for Non-Experts: With a natural language interface, even those without technical expertise can access sophisticated agricultural insights and recommendations.
- **Proactive Management:** Continuous monitoring and predictive models allow for proactive management, enabling farmers to address issues before they affect crop yield.
- Automation Potential: Function calling can automate tasks such as irrigation scheduling, fertilizer application, and pest control based on

real-time data, streamlining farm operations.

Challenges and Key Considerations for Data Accuracy and Actionability

Despite the promise of function calling in LLMs, several challenges must be addressed to ensure the data and recommendations are accurate, actionable, and trusted.

1. API Reliability and Data Quality

Data consistency and accuracy are paramount, particularly when relying on multiple external APIs. There must be robust mechanisms for validating and standardizing data from different sources, ensuring it is reliable for decisionmaking.

2. Latency and Timeliness

The value of real-time data depends on how quickly it can be retrieved and processed. Minimizing latency is critical, especially for time-sensitive decisions like irrigation during drought conditions.

3. Model Accuracy and Generalization

Predictive models must perform well across different regions and conditions. Ensuring that models are trained on diverse datasets and are rigorously evaluated is crucial for generalization.

4. Interpretability and Trust

Farmers need to trust the LLM's recommendations. Clear explanations for why certain decisions are suggested, along with transparency around the underlying data and models, are essential to build this trust.

5. Cost and Infrastructure

Accessing real-time satellite data and processing large volumes of information can be expensive. Developing cost-effective solutions and ensuring infrastructure availability will be key to widespread adoption, particularly in smaller or less developed agricultural regions.

6. Data Integration and Interoperability

Seamlessly integrating data from different sources — satellite imagery, weather stations, soil sensors, and farm management software — requires standardized formats and interoperable APIs. Fragmented data systems can hamper effective decision-making.

7. Security and Privacy

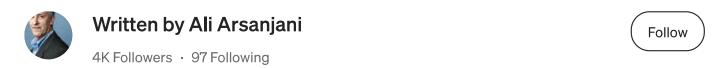
Agricultural data is sensitive, especially as farms adopt more technologydriven approaches. Ensuring secure data transmission, storage, and access is crucial to protect farmers' proprietary information.

Conclusion

The integration of function calling in LLMs for agriculture holds tremendous potential. You can leverage real-time data from satellites, sensors, and other sources, farmers can access timely, data-driven insights to optimize their operations. Note that, the road to realizing this vision requires addressing challenges related to data quality, model accuracy, latency, cost, and security. If you tackle these issues head-on, we can empower farmers to enhance productivity, resource management, and the sustainability of agriculture in the coming years.

AI systems employing Function calling in LLMs could positively impact how decisions are made on the farm, bridging the gap between cutting-edge technology and the age-old practice of agriculture. The future of farming is

digital, and with the right tools and infrastructure, it can also be smarter and more sustainable.



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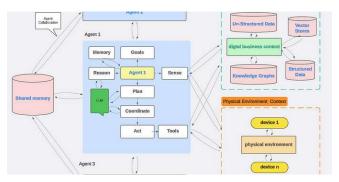




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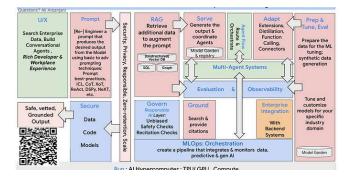




The Anatomy of Agentic Al

In this article we will elaborate on the anatomy of Agentic Al and how it operates.

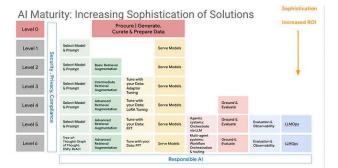
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The GenAl Reference Architecture







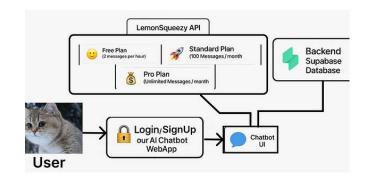
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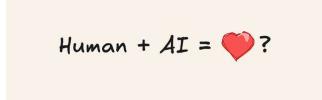
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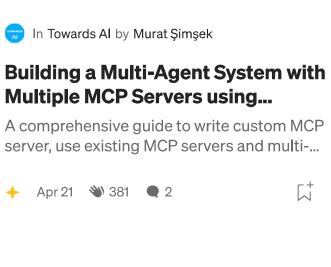




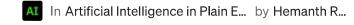
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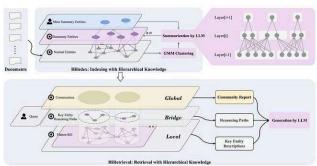




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