e-GRO Edible Alert



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A Primer of Artificial Intelligence for Greenhouse Control

Artificial Intelligence (AI) is disrupting industries by enabling computers to learn and perform tasks that once required human processing. In controlled environment agriculture (CEA), AI offers a potential to optimize crop management and environmental control for more efficient crop production, while some critical challenges remain for the full integration of AI into the existing CEA production systems.

AI encompasses various technologies, with Machine Learning (ML), Deep Learning (DL), and Generative AI (GenAI) being the driving forces (Figure 1). However, recent discussions around AI have predominantly focused on GenAI due to its ability to create new content such as text, images, and music by identifying patterns from extensive datasets available on the internet. Although the ability to generate realistic content is a significant milestone, GenAI is not intended for optimal process control and automation in physical environments. This article focuses on ML, a broader and more foundational category within AI, which has widespread applications across various domains including CEA. We will provide a primer on ML, explain why it is transformative to the CEA industry, and highlight current challenges to effective ML solutions for efficient greenhouse control.

A Primer on Machine Learning

Traditional greenhouse operations often require growers to manually program control rules into process control systems. Let's consider irrigation for greenhouse tomato as an example. Growers typically divide irrigation into various periods throughout the day, each associated with a different solar radiation-sum threshold. A common rule among growers is to maintain a stable drainage (leachate) ratio, for example 30% of the total irrigation volume. However, achieving a fixed drainage ratio is challenging because it is influenced by multiple environmental factors beyond solar radiation alone. As a result, growers frequently need to adjust parameters in response to changing weather patterns, relying heavily on their experience and intuition. They observe factors such as solar radiation and humidity throughout the day, along with historical drainage data, to make necessary adjustments.

In the context of ML, the initial step mirrors this human reasoning process by constructing a model that identifies how relevant features combine to influence the outcome (in this case, drainage ratio). For irrigation management, key features might include:

- Weather forecasts: Outside radiation, temperature, and humidity
- Crop parameters: Leaf area index altered by crop management (i.e., leaf pruning)
- Irrigation control parameters: Duration and radiation-sum thresholds

These features form the basis of a predictive model that estimates the crop transpiration rate and then expected drainage ratio given specific weather conditions and control parameters. A parameter-search algorithm can then

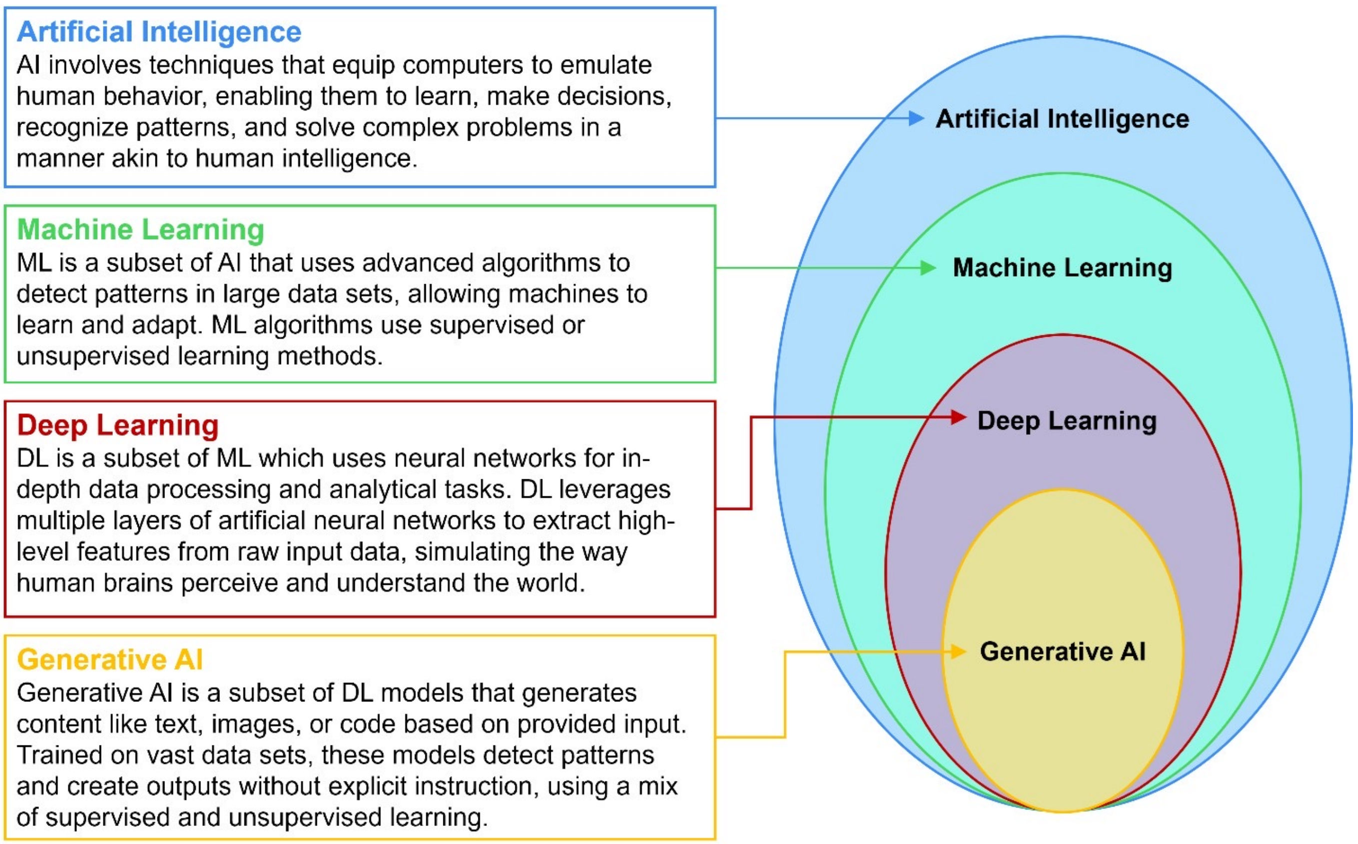

Figure 1. A hierarchy of prominent AI Technologies.

optimize climate and irrigation controls based on these parameters to achieve the target drainage ratio.

Constructing a model in ML provides an untrained model structure with unknown coefficients. The next step is to fit the model to historical data, uncovering patterns and learning the intricate relationships between the features and the outcome variable. This process, known as training, involves adjusting the model's coefficients based on historical data until it accurately predicts outcomes. After the training process, the previously unknown coefficients are determined, resulting in a trained model ready for practical application.

The above example provides a brief overview of the fundamental concepts of ML. While the modeling process can become quite complex, the essence of ML remains rooted in three core principles: human reasoning (constructing a model), statistical analysis (training the model), and automation (digitizing these steps in a computer). Essentially, ML mirrors the way humans reason, detect patterns, and make decisions.

Human in the Loop

As we transition from understanding the core principles of ML to exploring its

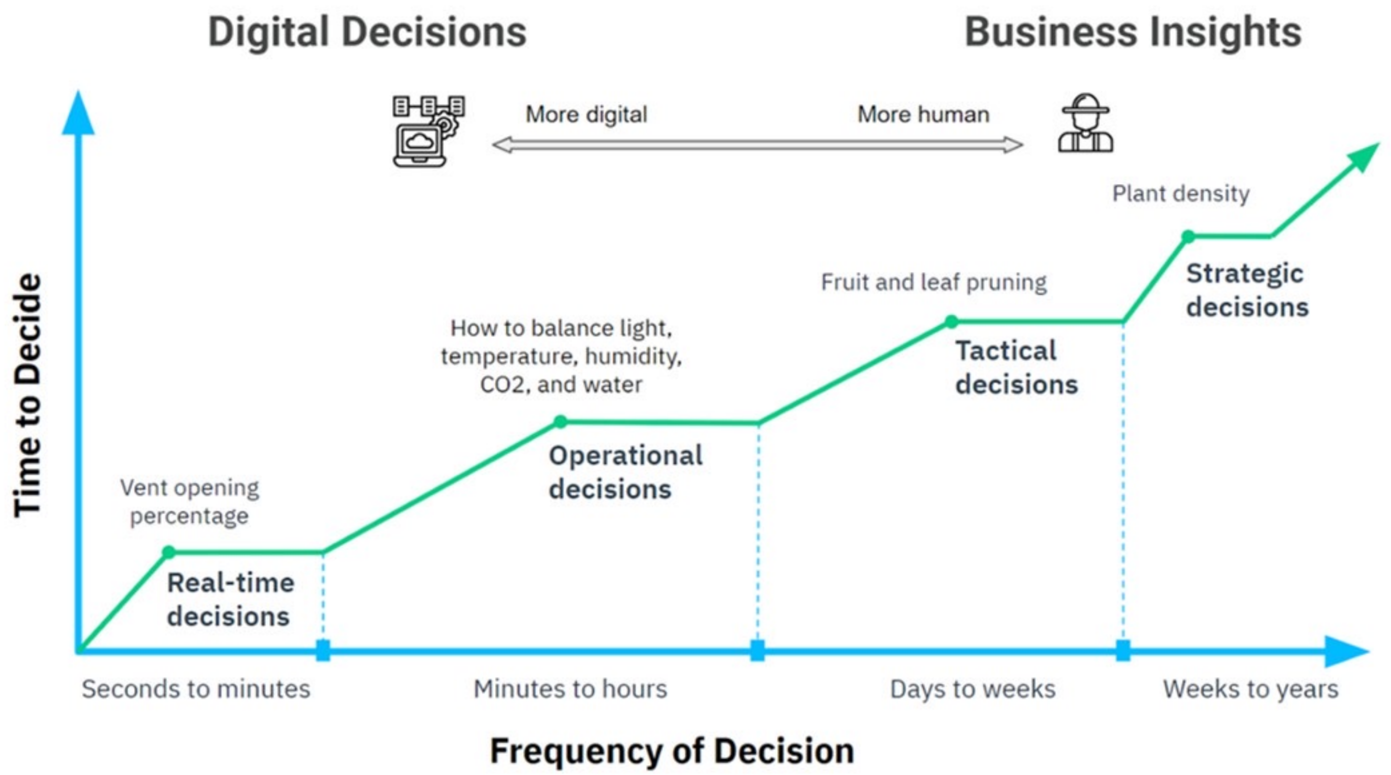

Figure 2. An illustration of different levels of decisions and their examples made in greenhouse crop production. We need both digital decisions and expert decisions (driven by business insights).

advanced applications, it is essential to acknowledge the unique strengths and limitations of both humans and ML.

Humans and smart machines are both remarkable learners, each with distinct strengths and weaknesses. Humans excel at understanding decision logic through insights—distilled data derived from mental shortcuts, oral or written accounts, or social codes—allowing them to quickly adapt to sudden changes. These insights, passed down through generations, enable sophisticated future simulations. Our neurons, trained by millions of years of evolution (analogous to techniques in ML) and education. (similar to "transfer learning" in ML), encapsulate knowledge so complex that machines struggle to deduce it independently, even with vast amounts of data. For instance, the theories of energy balance and thermodynamics, essential in greenhouse management, have been refined by humans over hundreds of years, a testament to the immense data and computation involved in human evolution.

The most effective AI solutions unify the power of ML with human knowledge to enhance decision-making processes. AI does not aim to replace humans but rather to assist in completing repetitive and laborious tasks. This enables growers to focus on key strategic decisions while AI handles lower-level tasks (aka “digital decisions”), as illustrated in Figure 2.

Challenges to AI-Enabled Autonomous Growing

Optimizing plant growth conditions necessitates a multidisciplinary approach combining growers' wisdom, scientific knowledge, and advanced data technologies. However, AI alone cannot solve all the challenges associated with greenhouse management. Robust data management systems are crucial to effectively address issues such as integrating legacy systems, handling data loss, monitoring control decisions, and ensuring data safety. Without these systems, AI systems will not have the foundation required to operate successfully.

Modern greenhouse operations collect an abundance of data, but currently struggle to consolidate data from their various operational systems in one place. A comprehensive data management platform designed to support greenhouse operations such as DataPilot developed by Koidra is necessary to help bridge the gap between traditional practices and modern AI technologies by providing robust tools for data integration, analysis, and risk management.

1. Integrating Legacy Systems

One of the challenges of implementing AI in greenhouse management is integrating legacy systems with new 3rd party technologies. Current centralized control systems were not designed to work with modern AI technologies. Integrating these systems requires a careful approach to ensure compatibility and functionality. A data management platform can create interfaces that allow data to flow smoothly between different systems and sensors. This ensures that AI models can access the necessary information to make accurate predictions and adjustments.

2. Handling Data Loss

Data loss is a common issue in greenhouse management. It can occur due to loss of power, sensor failures, network issues, or other technical problems. Handling data loss requires robust systems that can detect and compensate for missing data. This robustness is critical for maintaining the reliability and effectiveness of AI-driven greenhouse management systems.

3. Monitoring Control Decisions

Monitoring control decisions is essential for ensuring that AI-driven systems are working as intended. This involves tracking the actions taken by the system, analyzing their impact, and adjusting as needed. Comprehensive monitoring tools allow growers to track the performance of AI-driven control systems and to analyze system actions and their outcomes to identify and address any issues promptly.

4. Ensuring Data Safety

Data safety is a top priority in greenhouse management. AI-driven systems must be designed to operate safely, even in the event of technical failures or other issues. This involves implementing fail-safes and other safety mechanisms to protect plants and equipment. Without that, growers cannot rely on AI-driven systems to manage their greenhouses effectively and safely.

Future Perspectives

AI offers significant potential for transforming greenhouse management. By automating decision-making processes and integrating human knowledge, AI can optimize growing conditions, enhance productivity, improve crop quality, and ultimately improve profitability. The roadmap to autonomous growing involves a multidisciplinary approach, combining the wisdom of experienced growers and the results of scientific experimentation with advanced sensor, data, and control technologies. As AI continues to evolve, its applications in greenhouse management will undoubtedly expand, offering new opportunities for innovation, growth, and expanded earning potential in controlled environment agriculture.

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