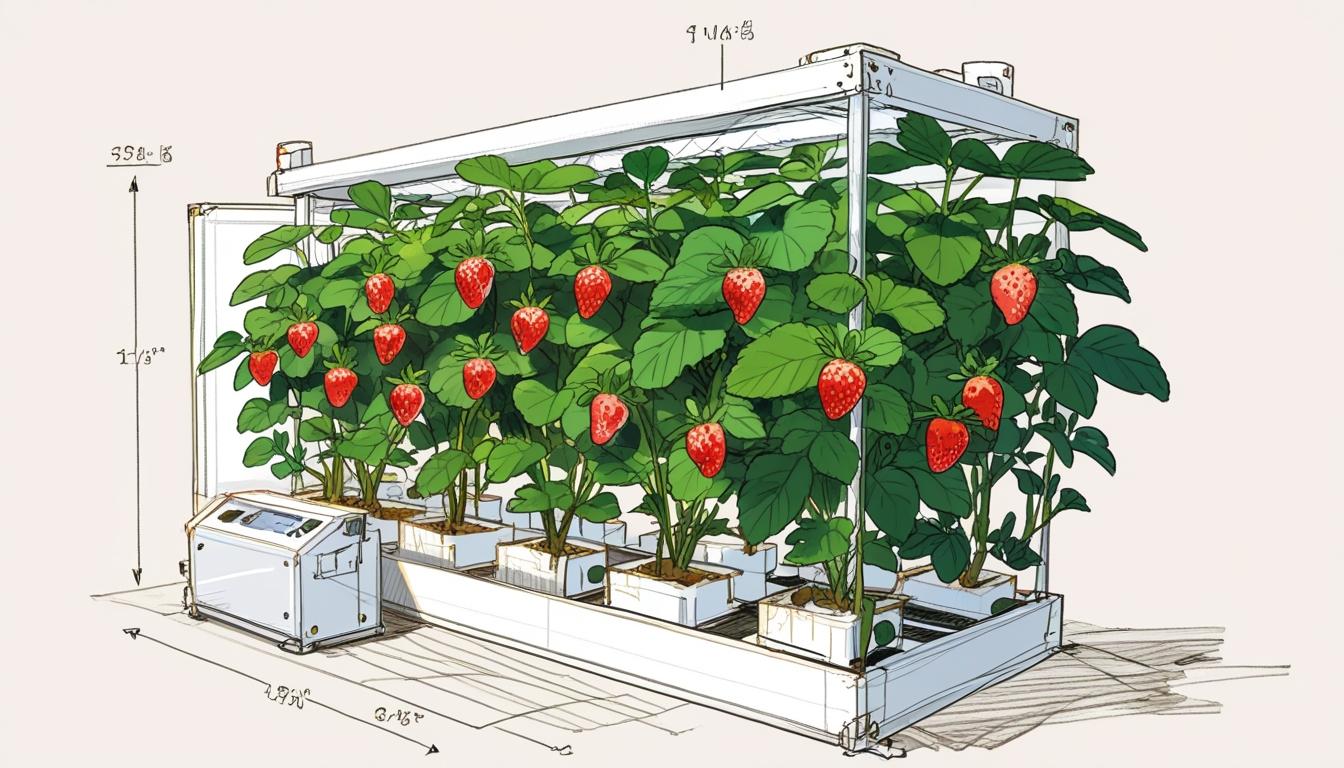
# Advancing nutrient management in strawberry cultivation with AI-driven growth stage classification



Nutrient management remains a fundamental component of modern agriculture, directly influencing crop health, quality, and overall yield. These factors are crucial not only for agricultural productivity but also for public health and global food security by assuring a stable and nutritious food supply. Advances in nutrient management have been supported by the adoption of cutting-edge, site-specific technologies that account for the spatial and temporal variations in soil nutrients. Proper nutrient application tailored to the specific growth stages of plants enables farmers to maximise outputs while avoiding the detrimental economic and environmental impacts of under- or over-fertilisation.

A noteworthy challenge within this field is the precise identification of plant growth stages, as each stage demands distinct nutrient profiles essential for optimal development. Incorrect timing or misclassification can result in diminished yields and lower quality crops, posing particular difficulties for high-value crops such as strawberries. Traditionally, this task has relied heavily on expert manual inspection, which is costly, susceptible to human error, and often unavailable to many growers. The rising use of greenhouses, driven by desires for controlled growing conditions and year-round production, has further accentuated the need for automated, accurate systems owing to the exacting nature of greenhouse environments.

Recent research has consequently shifted towards the integration of artificial intelligence (AI) to enhance nutrient management systems. AI technologies have found success in numerous agricultural domains—including stress and disease detection, growth monitoring, seedling classification, and yield prediction—yet applications specific to strawberry growth stage classification remain underdeveloped. The precise determination of strawberry development stages, such as flowering and fruit ripening, is vital for tailoring nutrient application schedules that maximize yield and improve fruit quality including size, flavour, and nutritional content.

Previous efforts employing AI for this purpose reveal several limitations. For example, a model based on YOLOv3 utilised UAV and near-ground imagery to classify seven strawberry growth stages from flowering to fruit rot. Although near-ground images achieved better detection accuracy due to higher feature resolution, the study was constrained by limited dataset size and lacked benchmarking against current state-of-the-art models. Another model, termed SDNet and based on YOLOX architecture, focused on five growth stages and demonstrated superior performance when compared to other YOLO variants. Additionally, a greenhouse-collected dataset featuring three growth classes—seedling, blooming, and crop—was introduced, comprising approximately 10,000 images. However, this dataset suffered from artificial plant arrangements that did not accurately reflect field conditions, limiting its real-world applicability.

A recent scholarly article reported in Nature distinguishes itself by concentrating specifically on nutrient management within contemporary greenhouse farming systems. This approach takes advantage of the controlled environment in greenhouses, where factors such as light, temperature, and humidity can be tightly regulated to create consistent and optimised conditions for plant growth. The study introduces a novel, high-quality dataset that captures seven defined growth stages of strawberry plants—from early flowering through to fully ripened fruit—each correlating with specific nutritional demands. Importantly, the dataset includes images taken under diverse lighting, weather, and background settings, enhancing its robustness and suitability for training and evaluating deep learning models.

The paper also undertakes a thorough benchmarking exercise involving multiple state-of-the-art deep learning classifiers, including classic convolutional neural networks, vision transformers, and hybrid models. Through a critical performance comparison, the study aims to establish a benchmark for strawberry growth stage classification and evaluate the practical implications of deploying these models in agricultural contexts, considering scalability and operational constraints.

In outlining the organisation of the research, the authors note that the dataset collection and preprocessing methods are discussed in detail in Section 2, followed by experimental setups and results in Section 3. Section 4 provides an in-depth discussion of the results, emphasising the advantages and limitations of the different AI approaches, while Section 5 offers concluding remarks and directions for future research.

This work signifies an important advancement in the intersection of AI and precision agriculture, particularly in supporting nutrient management within controlled-environment agriculture. By focusing on a comprehensive dataset and evaluating cutting-edge AI models, the study provides valuable insights and tools that could enhance the productivity and sustainability of strawberry cultivation, with potential implications for other crop species as well.

Source: [Noah Wire Services](https://www.noahwire.com)

## Bibliography

1. <https://www.farmers.gov/conservation/nutrient-management> - Supports claims about nutrient management's role in optimizing crop productivity, reducing environmental impact, and the importance of site-specific plans using the 4Rs framework (right source, method, rate, timing).
2. <https://www.nrcs.usda.gov/getting-assistance/other-topics/nutrient-management> - Corroborates the economic and environmental benefits of nutrient management, including maximizing yields while minimizing ecological harm.
3. <https://www.farmers.gov/blog/save-money-and-protect-water-quality-with-smart-nutrient-management> - Validates the $30-per-acre savings claim from optimized nutrient management and highlights USDA's emphasis on precision agriculture for cost reduction and emissions mitigation.
4. <https://ipcm.wisc.edu/wp-content/uploads/sites/54/2022/11/Benefits-of-an-NMP.pdf> - Provides evidence for profitability improvements through nutrient management plans, aligning with the article's focus on economic and yield benefits.
5. <https://drawdown.org/solutions/nutrient-management> - Substantiates claims about global food security (through yield increases) and environmental co-benefits (soil health, reduced emissions) from improved nutrient practices.
6. <https://www.farmers.gov/blog/save-money-and-protect-water-quality-with-smart-nutrient-management> - Further confirms the $30-per-acre savings figure and connects nutrient management to greenhouse gas reduction, supporting the article's sustainability claims.
7. <https://news.google.com/rss/articles/CBMiX0FVX3lxTE5yc0ZkQUVCMHl1TktWMHFseU5YUEJDckpZVTFhOFY5aVNXVnA4ZzFqZEM5MFNFMVJzTkZLanpzb184Q2RzU0piUUlLb20zUUlQWFNGUTg0M2hDcHkzZEVz?oc=5&hl=en-US&gl=US&ceid=US:en> - Please view link - unable to able to access data