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AI in Agronomy: From Crop Diagnosis to Yield Prediction

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INTRODUCTION

The practice of agronomy has always been based on the closely observing crops, soil, weather and field conditions. Artificial intelligence is augmenting agriculture by transforming massive amounts of farm data into actionable and timely advice. Photos taken by smartphones, drones and satellites can show crop stress, and sensors track soil moisture and field microclimates. Machine-learning algorithms integrate these observations with weather forecasts and management data to identify issues, suggest treatments and predict yield. AI does not replace the agronomist or farmer, it enhances their ability to observe, compare and respond.

What Does AI Mean in Agronomy

AI is a set of technologies that process the data through pattern recognition and learning to support decisions. Machine learning reveals relationships between soil, crop, weather and management factors. Deep learning processes complex images and time-series data, and computer vision identifies objects, symptoms and within-field variability. Generative AI can be used to explain complex technical information in simple language and respond to basic queries. When connected with remote sensing, the Internet of Things, geographic information systems and crop models, AI creates a continuous link between field observation and agronomic action.

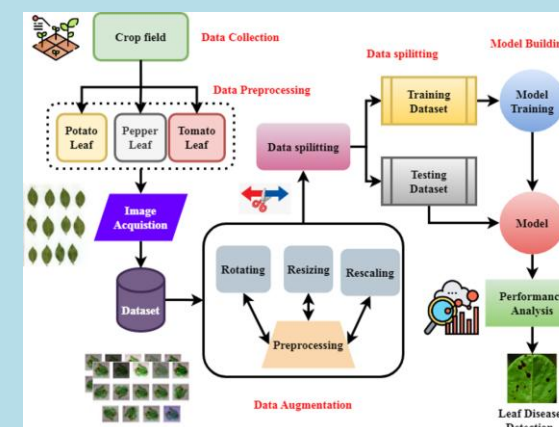
The Data Behind Intelligent Farming

Every AI recommendation starts with data. Satellites monitor growth of vegetation on a large scale, and drones take high-resolution images of single fields.

Close-up photos of leaves, insects and symptoms are taken with smartphones. Soil sensors detect moisture, temperature, salinity, and occasionally nutrient-related attributes. Rainfall, humidity, solar radiation and wind are recorded by weather stations. Historical yield, date of sowing, variety, fertilizer application, irrigation and pest management records are a vital part of the context. The fusion of the two sources tends to yield more reliable decisions than that obtained by a sole image, sensor or vegetation index.

Rapid Crop Diagnosis

AI-enabled crop diagnosis relies on computer vision to analyze visual indicators like spots, lesions, chlorosis, wilting, curling, stunting and anomalous growth. A farmer can take a picture of an infected plant and a trained model will list potential diseases, nutrient disorders or pest damage. Camera-equipped drones can quickly cover large fields and flag suspicious areas for a closer look. This shortens scouting time and allows agronomists to focus on high-risk areas. However, some symptoms are mimicked by others and thus knowledge of field history, weather, soil, and confirmation by experts are still required prior to application.



Detecting Stress Before Serious Damage

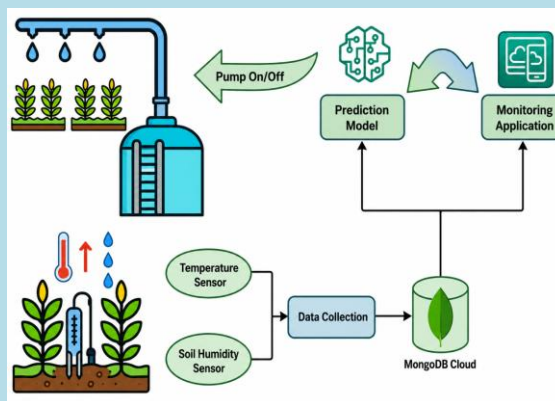
Plants are routinely stressed before overt symptoms occur. Thermal imaging can also detect warm canopies, indicative of water stress or reduced transpiration. Multispectral and hyperspectral sensors are able to identify reflectance changes associated with loss of chlorophyll, nutrient deficiency, disease progression and/or tissue injury. AI models can interpret these faint signals and identify stress clusters. Once the ailment is detected, farmers can visit the affected areas, apply corrective irrigation, test the nutrient levels or even start with specific protection measures before the disease has a chance to spread. The objective is not just to enable faster diagnosis, but earlier and more cost-effective intervention.

Smarter Soil and Nutrient Management

Uniform application of fertilizer neglects the inherent variability of fields. Based on soil-test results, crop growth, yield maps, topography, weather and sensor data, AI can predict where the nutrient supply is too low or too high. Decision-support systems then advise suitable rates, sources, application timing and methods. Nutrient-deficiency symptoms can be identified with some image-based applications, but visual diagnosis should be confirmed as drought stress, root damage, or disease can cause similar symptoms. When used appropriately, AI contributes to balanced nutrition of crops, enhances nutrient-use efficiency and reduces superfluous fertilizer investment and environmental loss.

Precision Irrigation

Irrigation water demand for crops is predicted by AI-based irrigation systems using soil moisture, temperature, humidity, rainfall forecasts, evapotranspiration, crop stage, and canopy status among others. Now, instead of watering by the calendar, farmers can water when and where the need is greatest. The models can also identify abnormal moisture patterns, due to blocked emitters, leaks, poor drainage or uneven application. Proper timing of irrigation contributes to protecting crops during vulnerable stages of development and conservation of water and energy. Local calibration is still necessary as soil texture, root depth, irrigation system and sensor location within the field have a significant impact on recommendations.



Targeting Weeds, Pests and Diseases

Computer vision can separate crops from weeds to inform spot spraying or mechanical weeding. Smart insect traps take photos and count selected pests on their own, and weather-based models calculate when infection or infestation pressure is mounting. Sprayers with AI can target individual plants rather

than spraying an entire field. Such methods cut down on scouting labour and pesticide application that may not be needed. However trap counts and image detections need to be interpreted with crop stage, natural enemies, economic thresholds and field observations. AI needs to support integrated pest management and not automatic chemical usage.

From Crop Monitoring to Yield Prediction

Yield prediction is one of the top-priority applications of AI in agronomy. Models integrate historical yield, weather, soil properties, crop variety, planting date, management practices, and remote sensing-based indices including canopy cover, leaf area, and vegetation vigor. Machine-learning models can identify complex patterns and interactions that simple averages may fail to capture. Updates can be made to predictions as additional weather and crop-growth information becomes available during the season. Early forecasts are used for input planning, labour hiring, storage, transport, insurance and marketing, and late forecasts for harvesting and supply chain management.

A yield prediction is not a promise. Its accuracy varies with the quality of data, crop growth stage, forecast length and the dissimilarity between present conditions and the conditions when the model was trained. Predictions therefore should be presented as a range with an upper and lower bound and the degree of confidence associated with the prediction rather than a single point. Hybrid systems that integrate AI and crop-growth models seem to be particularly promising as they link observed patterns directly with biological processes such as development, water balance, photosynthesis and biomass accumulation.

Turning Prediction into Action

A useful AI system must answer three practical questions: What is happening? Why is it happening? What should be done next? A stress map alone has limited value unless it guides scouting, sampling or management. A rainfall forecast becomes useful when linked with sowing, irrigation, fertilizer or spraying decisions. A yield prediction matters when it improves procurement, storage or marketing. Effective platforms therefore convert complex analysis into simple, location-specific actions while explaining the evidence, expected benefit, uncertainty and possible risk.

Opportunities for Small and Marginal Farmers

There's no need for farmers to own costly technology to use AI. Farmer Producer Organisations (FPOs), cooperatives, Custom Hiring Centres (CHCs), agri-startups and extension providers could offer drone mapping, precision spraying, soil testing and digital advisory as shared or pay-per-use services. With just a single smartphone application, or voice-based services, farmers are able to receive guidance in their local languages at a fraction of the cost. Offline functionality, simple interfaces and human assistance are especially valuable in areas with limited internet access and digital literacy. Shared access to resources could transform high-tech machinery into a high-value agronomic service.

The Human Expert Remains Essential

Artificial intelligence is good at identifying patterns rapidly, but it can stumble when faced with new strains, novel diseases, composite symptoms, low-

quality images or unexpected weather. Models trained on clean lab images may fail when they encounter dust, shadows, overlapping leaves and complex backgrounds in the field. Biased or incomplete data can also lead to misleading advice. Farmers, agronomists, and extension workers need to confirm critical diagnoses, particularly prior to using pesticides or taking other costly actions. The best system is one that marries the computational power with the knowledge gained in the field, scientific expertise and farmer observations.

Building Trustworthy AI

Trustworthy agricultural AI needs to be accurate, interpretable, validated locally and transparent in terms of uncertainty. Farmers need to know what information is being collected and how that information is being used and if it is shared with other entities. Data ownership, privacy, cybersecurity and commercial influence require similar consideration in the farm context. Advice needs to be evaluated through multiple seasons, sites, crops, and farming systems. Success should be measured not just by the precision of models, but also in terms of profitability, resource savings, environmental consequence, usability and the farmers capacity to take action.

The Next Frontier

The next era of AI will bring together real-time sensors, satellite imagery, drones, autonomous machinery, crop models and weather forecasts in adaptive decision-support systems. Edge AI will process data on phones, cameras, or farm machinery, allowing faster operation at the edge with minimal

connectivity. Explainable AI will identify the factors that led to a diagnosis or prediction. Digital twins may test alternative sowing dates, irrigation schedules, and nutrient regimens before action is taken. These and other improvements could move agronomy from reacting to visible damage to predicting risk and avoiding loss.

A Smart Adoption Checklist

Before adopting an AI tool, ask:

- Does it address a genuine field problem
- Has it been validated for the crop and region
- Can farmers understand and act on its recommendation
- Does it indicate uncertainty and possible errors
- Can important results be verified in the field
- Are data privacy, cost and technical support clearly explained
- Does it improve profit, efficiency or resilience

CONCLUSION

AI is turning agronomy from periodic observation into continuous, data-enabled management. It can tell when crops are stressed, when and how much to irrigate and fertilize, when to treat for pests and weeds and even how much they will produce before they are harvested. Its real value, however, relies on accurate information, local validation and timely action. The future is not farming without people it's farming where farmers and agronomists detect problems earlier, understand fields more deeply and make better decisions with more confidence.