Agriculture and Artificial Intelligence

How to Effectively Implement AI in Precision Agriculture

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Introduction

It seems that everywhere you look these days someone is talking about Artificial Intelligence (AI). How will AI transform our experience at the grocery store? Will AI make certain professions obsolete? Can an AI tool write this paper better than a human? Just like every other industry, AI is being utilized in agriculture and its prevalence is increasing rapidly.

This paper will delve into the subject of AI in agriculture and discuss two main questions:

1. Why is the implementation of AI models in agriculture different from its implementation in other industries?
2. What are the unique challenges that the agriculture industry presents to AI algorithms and models?

This paper is based on more than seven years' worth of knowledge that Taranis has amassed in the field of agriculture, implementing AI solutions to monitor the growth and health of crops, and working with the farming community.
In what follows, we present some of the major obstacles that impede the implementation of AI in precision agriculture, as well as strategies to overcome them.

Gershom Kutliroff, an expert in computer vision and artificial intelligence, serves as CTO of Taranis. Prior to joining Taranis, he was the CTO and co-founder of ClearVuze where he developed autonomous drone solutions, and he was CTO of Omek Interactive, a Human-Computer Interaction company acquired by Intel in 2013. He is an inventor on over 25 issued patents. He earned his Ph.D. and M.Sc. in Applied Mathematics from Brown University, and his B.Sc. in Applied Mathematics from Columbia University.

AI and Agriculture:

The Current Landscape

Often considered the oldest industry in the world, agriculture has evolved gradually and has been the catalyst for great innovations. Perhaps the agriculture industry has adopted AI tools at a slower pace than other industries, however, a new era is fast approaching, and the past few years have seen a major upsurge in breakthrough technologies, start-ups, and applications of AI in agriculture (Sparrow et al., 2021).

Currently, some of the main uses of AI in farming are:

Precision Agriculture: Utilizing data and AI technology to optimize crop yields, reduce costs, and minimize environmental impact. For instance, data collected by drone images and analyzed by an AI model can be used to improve weed and disease management.

Crop and Livestock Management: Using AI to monitor and manage crops and livestock, including identifying pests and diseases, and optimizing feeding and breeding. For instance, robots powered by AI can be used to optimize a task like milking cows.

Autonomous Vehicles and Robotics: Using AI to control and operate autonomous vehicles and robots for tasks such as planting, harvesting, spot spraying, and soil analysis.

Weather and Climate Monitoring: Using AI to analyze weather patterns and predict weather events, in order to optimize crop and livestock management.

Supply Chain Management: Utilizing AI to optimize logistics and distribution in the agricultural supply chain, including predicting demand and managing inventory.

There are many benefits to utilizing AI tools in traditional agricultural tasks. For instance, increased efficiency in the detection of crop diseases and weeds optimizes the use of herbicides and fungicides. This in turn lowers costs for the farmers and reduces the environmental footprint of the operation. AI tools can also help farmers address labor shortages by using autonomous machinery, robots, and more efficient work processes to shorten or completely change the nature of many time-intensive tasks.

The integration of AI into the food supply chain offers benefits to consumers, such as reducing crop wastage and allowing for a more efficient and smarter value chain in agriculture.

AI is an increasingly important tool being used to help farmers optimize agricultural output, efficiency, a sustainability, and society stands to benefit from a more sustainable an secure food supply.
(Sparrow et al., 2021)

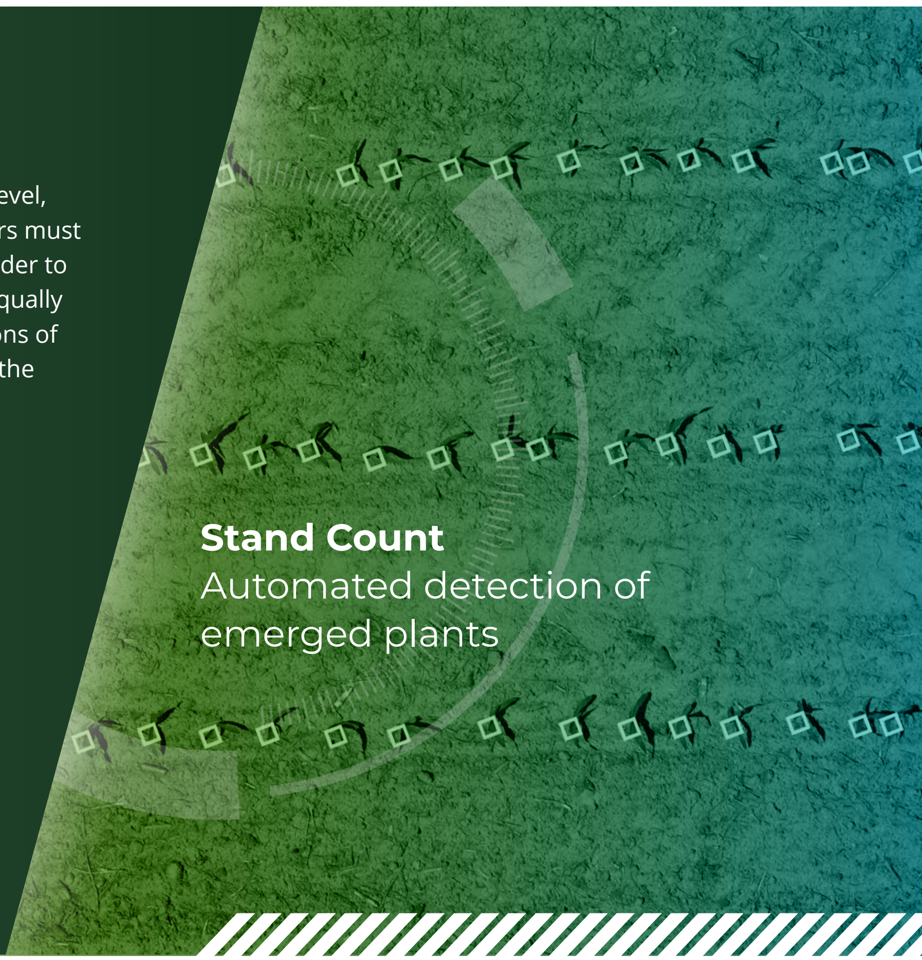
AI and Precision Agriculture

The concept of Precision Agriculture has been around for approximately 30 years. Precision Agriculture is a farming management approach that uses data, technology, and other means to help farmers make calculated and precise crop management decisions.

It involves collecting and analyzing data on factors such as soil conditions, weather, and crop growth, and using this information to make informed decisions about planting, fertilizing, pest management, and harvesting. It includes methods such as crop scouting, variable rate technologies, soil sampling, and drip irrigation, which aim to optimize the use of inputs, enhance soil health, accelerate decision-making, and ultimately improve crop yield.

In order to take Precision Agriculture to the next level, where it can be deployed on a larger scale, growers must be able to obtain insights in a timely manner in order to allow for quick decision-making and action; and equally important - quickly adapt to the changing conditions of farming. This is especially critical when looking at the global need to increase food production.

In the past, many problems that farmers faced, such as diseases and weeds, were solved with the invention of new chemicals or new GMO (genetically modified) seed varieties. These solutions add expenses to the farmers' already tight budgets. Some of the common problems faced by farmers can be solved efficiently and sustainably by combining AI and Precision Agriculture principles.



With the advances that AI has made in the past few years, it has the potential to be the driving force behind the next revolution in agriculture.

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The Unique Challenges in Applying AI Models to Agriculture

The quality and character of the data used to train AI models is arguably the most critical factor that determines their performance. In particular, the ability of the models to detect and classify relevant phenomena is dictated by the extent to which the training dataset reflects the data subsequently captured in the production environment. For this reason, gathering a rich and diverse dataset – and subsequently annotating (i.e process of labelling the data and helping machines make sense of text, video, image, or audio data) this data in a consistent manner – occupies a significant amount of time and effort from AI practitioners.

In the context of using AI to provide solutions in agriculture, gathering a sufficiently rich dataset means capturing imagery under a large range of environmental conditions, including varying lighting, different seed varieties, soil types, and geographical regions. Moreover, the unique nature of agriculture requires that AI teams approach the collection of training data (both initial and ongoing) differently than in other areas of AI. Below we discuss two challenging aspects of this data collection effort, and offer some solutions, based on our own experience, to help overcome them.

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Short Time Window to Train AI Models

Consider an AI solution that is designed to detect early emergence of plants in the field, or, post-emergence, to identify weeds and symptoms of disease. Due to the seasonal nature of the growing season, collecting sufficiently rich data representing these phenomena must be timed to the relevant growth stages of the crop, when emerging crops, or weeds and diseases, are visible.

In practice, row crops such as corn and soybeans tend to grow quickly during the season, so the windows in which to gather data can range from only one to three weeks each year.

The challenge of getting to fields during these short windows and collecting sufficient training data is compounded by two additional factors: the dependence of this time window on the field's planting date – which varies across different fields – and the need to gather a large number of samples over a short amount of time from across a wide geographical region such as the U.S. Corn Belt.

Overall collecting the data can be challenging because of these time constraints, yet critical for effectively applying AI detection models.

The Unique Challenges in Applying AI Models to Agriculture

Data Drift

Once the dataset is collected, it can be annotated in order to specify the phenomena of interest in the field. In our scenario, this means marking the locations of the images where plants are emerging, as well as visible weeds and symptoms of diseases.

The annotated data can then be used to train AI models to detect these phenomena automatically when deployed to production, and modern, deep learning-based models perform remarkably well at these tasks.

Notably, this is true only insofar as the data captured in the production environment continues to reflect the distribution of the training dataset. In practice, however, the performance of AI models tends to suffer from a phenomenon known as data drift. As per Duckworth, et al.:

> *Predictive algorithms deployed in dynamic environments are subject to data drift, defined as a systematic shift in the und rlying distribution of input features... data drift can invalidate a model, as the drifted feature distribution may predominantly lie in a region where the model poorly performs (Duckworth et al., 2021).*

While data drift is common to many industries in which AI solutions are deployed, and often causes a degradation in the performance of the models over time, it is particularly present in agriculture. Because of the inherently dynamic nature of a biological system, the distribution of agricultural data is constantly in flux. We can point to numerous factors that contribute directly to this changing character of the data.

Certain strains of weed species can develop an immunity to herbicides, or new herbicides may be introduced to the market. Alternatively, growers may change their farming practices, for example by adopting no-till farming. All of these changes will alter the distribution of weed species in growers' fields.

Similarly, new diseases can appear and spread during a growing season, or the adoption of different seed strains may increase or decrease the prevalence of certain diseases. As an example, a fungal disease of corn known as Tar Spot was first discovered in the U.S. in 2015 and has since caused serious economic damage throughout much of the Midwest (University of Maryland, 2022.)

The Unique Challenges in Applying AI Models to Agriculture

To appreciate the way in which data can drift over time, refer to the below figure, which displays a collection of images containing symptoms of the disease Brown Spot in soybean plants, gathered over two successive seasons, and projected onto a two-dimensional graph. The color of each data point corresponds to the season in which the data was collected.

Although the images are all from the same crop (soybeans), and exhibit the same disease symptoms (Brown Spot), there is already clearly a drift in the distribution of the data from one season to the next, and this drift is likely to increase over successive seasons. Because of data drift, it is necessary to continuously re-train AI models in order to adapt to the changing data distributions and avoid a degradation of performance over time.

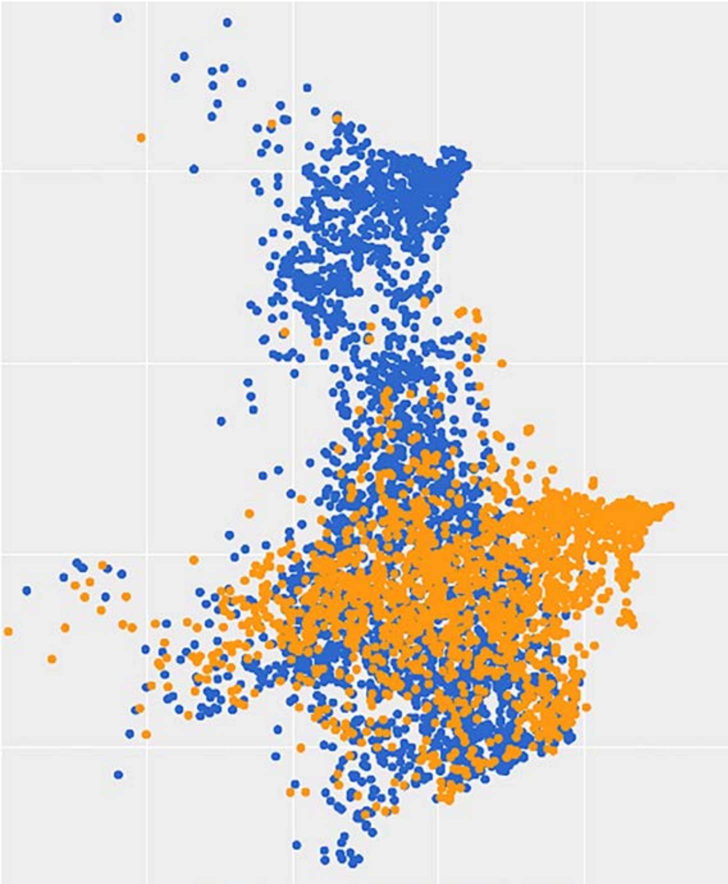


Figure 1: A plot of the images containing Brown Spot of Soybean disease over two successive seasons. The colors correspond to the season in which the image was captured. (Images were projected to two dimensions).

Case Study:

AI-Powered Crop Intelligence

Taranis empowers growers with a sophisticated understanding of what is happening in their fields, so that decisions are made on the basis of real and timely data. To this end, Taranis scouts growers' fields with drones and small planes, gathering high-resolution imagery of every acre, and then applying AI models to analyze the imagery to determine the plant population, detect weed pressure, diseases, nutrient deficiencies, and other threats. Over the years, Taranis has captured more than 200 million data points, and growing, and is using this dataset to train its AI models.

As the company has encountered the particular factors described above that characterize the agricultural industry, it has adapted both its business model, as well as its AI solutions, accordingly. These aspects of Taranis' solution have been critical in enabling the company to provide customers with meaningful and actionable insights across millions of acres.

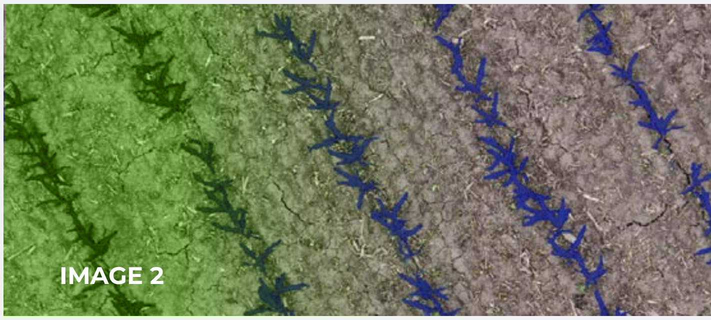
Below we discuss how Taranis has addressed some of these challenges in obtaining and maintaining a high-quality dataset for agriculture.

Ensuring Data Quality

Taranis offers a full-service business model in which the company partners with a large network of drone service providers (DSPs) to directly capture imagery of customers' fields.Crop growth models based on individual planting dates as well as regional weather patterns are used to determine the optimal time windows in which to arrive at growers' fields, and pilots are directed to fields accordingly, to capture the leaf-level imagery and then ensure the images are promptly uploaded to the company's servers for processing.

Managing a logistical operation of this scale is an essential element in the company's ability to scout customers' fields and generate actionable insights in a timely and reliable manner.

This full-service model has important implications for the development and deployment of Taranis' AI solutions, as well. Direct management of pilots' schedules and their arrival at growers' fields during the relevant crop growth stages allows for the collection of the rich, large, and diverse datasets necessary in order to train the AI models. Moreover, because the images for production are captured in the same way as those used in the training datasets, the data distributions are highly correlated, and this is reflected in the high performance of the AI models in production.



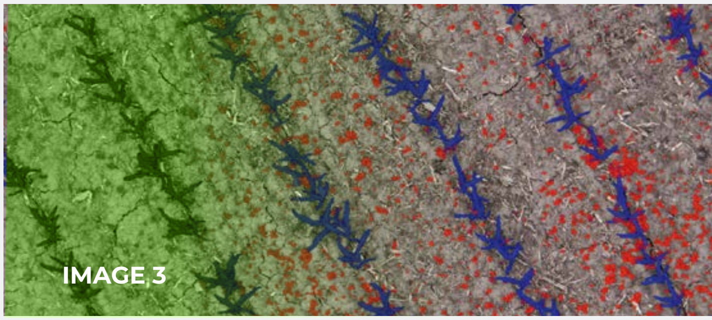


Image 2: An image of a corn field analyzed with AI. Th pixels corresponding to the corn plants are colored blue.

Image 3: An image of the same corn field. The pixel corresponding to weeds are colored red.

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Case Study:

AI-Powered Crop Intelligence

Adaptable AI Solutions

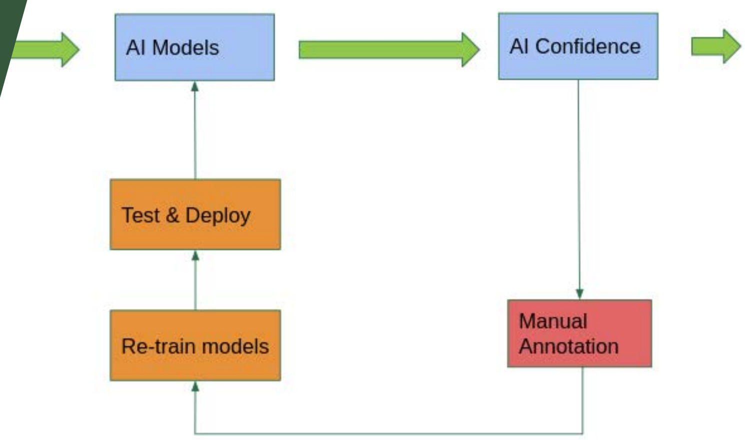
In order to address the problem of data drift, Taranis employs an approach known as continuous learning. The idea of continuous learning is straightforward: instead of training an AI model once and then deploying it and "forgetting about it", data from production is saved and used to continuously refine the model parameters. This maintains a high correlation between the distribution of the data used to train the model and that captured during production. Not surprisingly, however, the devil is in the implementation details, and we will mention two key aspects of assembling our continuous learning infrastructure.

The first is our ability to automatically identify the data coming from production that is not correlated with the training dataset. This is a non-trivial task when considering that in a single day, hundreds of thousands of images may be captured, and only a very small percentage of them should be used in order to refine the AI model.

We use a combination of several techniques to identify the images that should be used for re-training, which we collectively term the "AI Confidence" component. These techniques include "out-of-distribution" models that detect whether an image appears to have come from the same distribution as the training set, as well as techniques that analyze the results of our insights to identify anomalies.

The second challenge we encountered when designing a continuous learning flow involves the automatic re-training and deployment of the refined AI models, once the new data has been added to the training datasets. The dynamic nature of agriculture, combined with the seasonal character of the business, dictates re-training and deploying the refined AI models to production as quickly as possible. To this end, it has proven crucial to support a fully automated process to re-train the models, and then to validate the model predictions across a broad range of test data, to ensure there is no degradation in performance.

To the right is a high-level diagram of a continuous learning workflow. Images are first processed by the relevant AI models and then passed to the AI Confidence component in order to identify which images should be used to refine the models. A small percentage of the total images from production are thus selected to be added to the relevant training dataset. These images are annotated manually, and then the model is automatically re-trained, tested and deployed to production.



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What’s in Store for the Future

As camera-based AI solutions continue to address many different areas of farming and crop management, we can expect to see a similar virtuous circle as we have witnessed in other industries. In particular, the effectiveness of AI leads to the increased deployment of cameras and the infrastructure to support them, which then lowers the cost of camera systems and further encourages their usage. In turn, the availability of cheap, high quality cameras makes it easier to develop and support AI applications.

In a similar way, we will see cameras integrated into more and different types of farm equipment, easing the collection of data, speeding up the development of AI algorithms, and thus paving the way for additional AI solutions that will further strengthen the farmer’s understanding of what is happening in his/her fields. This process will speed the adoption of Precision Agriculture technologies and practices, and, subsequently, will positively impact the farmer’s bottom line, as well as the environment in general.

About Taranis

Taranis is the world's leading AI-powered crop intelligence platform, 100% focused on helping Ag advisors demonstrate value to their growers and build better relationships through full-service, leaf-level data capture. Taranis' insights allow them to accelerate decision making, simplify management, and improve their bottom line. Since its founding in 2015, Taranis has worked with the world's top agricultural retailers and crop protection companies, serving millions of acres for customers in the United States, Brazil, and Europe. Taranis has offices located in Westfield, Indiana, Tel Aviv, Israel, and Campinas, Brazil. To learn more visit www.taranis.com.

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