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DIGITAL AGRICULTURE IN ACTION

ARTIFICIAL INTELLIGENCE FOR AGRICULTURE

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PREFACE

This publication on artificial intelligence (AI) for agriculture is the fifth in the *E-agriculture in Action* series, launched in 2016 and jointly produced by FAO and ITU. It aims to raise awareness about existing AI applications in agriculture and to inspire stakeholders to develop and replicate the new ones. Improvement of capacity and tools for capturing and processing data and substantial advances in the field of machine learning open new horizons for data-driven solutions that can support decision-making, facilitate supervision and monitoring, improve the timeliness and effectiveness of safety measures (e.g. use of pesticides), and support automation of many resource-consuming tasks in agriculture.

This publication presents the reader with a collection of informative applications highlighting various ways AI is used in agriculture and offering valuable insights on the implementation process, success factors, and lessons learnt.

The articles are original submissions written by authors representing companies, universities or private entities. The narrative and the views are solely those of the authors and in no way confer endorsement by FAO or ITU. The chapters displaying applications were edited for style and for clarity but were in no way edited to modify the narrative from the original submission. We have tried to maintain the original narrative style of each contributor. Neither FAO nor ITU promotes or endorses any of the statements, comments and products or applications mentioned in the articles. The aim is solely to share information and make readers aware of some of the information communication technology applications out there and to facilitate understanding of AI and its possible applications.

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Adopting artificial intelligence solutions for agriculture: potential, the process, the success factors, and key recommendations

Aziz Elbehri, Hani Eskandar and Roman Chestnov

Agriculture – a new old priority?

The year 2020 marked the start of the Decade of Action to deliver the United Nations (UN) Sustainable Development Goals (SDGs) by 2030. Agriculture is one of the sectors that requires substantive change to accelerate a response to the key barriers that impede sustainable development. (De Clercq et al., 2018)

Rapid evolution of artificial intelligence (AI) technology offers a new tool for making agricultural practices more efficient, equitable and less damaging to the environment at a time when progress is critical to achieve the targets set by the global community.

According to the 2020 SDGs Report, the world is not on track to meet these SDGs, and the ongoing COVID-19 pandemic has only exacerbated some of the gravest global challenges, including hunger and poverty. (United Nations, 2020)

In 2019 there were an estimated 690 million undernourished people, nearly 60 million more than 2014. (United Nations, 2020) A 2021 UN report on food insecurity in the world estimated that in 2020, between 79 to 161 million more people were facing hunger than in 2019 and an additional 6.9 million children were affected by wasting. Overall, there has been a spike in moderate or severe food insecurity (based on the Food Insecurity Experience Scale) which rose from 26.6 percent in 2019 to 30.4 percent in 2020, with negative repercussions for health and well-being. (FAO, IFAD, UNICEF, WFP, and WHO, 2021)

Reversing the above trend is a high priority not just to alleviate the burden of hunger and malnutrition, but also to ensure sustainable economic and social progress. One in four workers in the world is employed in agriculture and in over a quarter of low- and middle-income countries (LMICS) agriculture contributes 20 or more percent to national GDP. (World Bank, 2020) Yet, over 400 million small-scale farmers live in poverty and face severe shortages of financial resources and food. (Lian, 2019) Although small farmers are among the key suppliers of food, their incomes and productivity are consistently lower than those of larger producers, due to poor access to tools and resources and greater vulnerability to external shocks. The COVID-19 pandemic has had a disproportionate effect on these farmers, leading to the collapse of many local markets and supply chains on which they relied. (United Nations, 2020) Urgent support must be provided to small-scale farmers to enhance food supply and maintain their livelihoods.

A boost to agricultural production must not come at the expense of the environment. Agricultural activity remains one of the major sources of CO_2 emissions, many of its conventional practices drive global deforestation and result in water and soil pollution, thereby putting many lifeforms at risk and contributing to climate change.

At least seven of the seventeen UN SDGs are, therefore, directly linked to agricultural activity: SDG 1 (end poverty); SDG 2 (zero hunger); SDG 8 (decent work and economic growth); SDG 12 (responsible consumption and production); SDG 13 (climate action); SDG 14 (aquatic life); and SDG 15 (life on the land). In addition, agriculture has an indirect impact on global health (food quality being one of the disease risk factors), gender equality (through its potential to increase access to resources and employment for women and children); and infrastructure (acting as a driver of local infrastructural development).

In this context, innovation in agriculture emerges as a crucial priority and an essential component of post-COVID-19 recovery. Connecting remote rural areas remains one of the top priorities, and global stakeholders need to leverage every tool to make existing farming and livestock activities more efficient and sustainable.

Artificial intelligence: a new tool for agriculture

Recent scientific advancements, breakthrough results and the success of particular applications have brought artificial intelligence (AI) into the spotlight. AI systems are already being deployed or piloted in many sectors including automotive, financial, manufacturing, health, security, and government.

What is AI?

Simply put, AI refers to a family of technologies that allow computers and other machines (e.g. robots) to perform tasks previously thought to rely on human experience, creativity and ingenuity. It involves the ability of machines to function autonomously, and "learn" from large volumes of input data, without being explicitly programmed for the required task.

In most AI systems, learning happens by continuous adjustment of a broad set of parameters based on training data to show the system the correct output expected when provided with a given input. This involves the use of machine learning algorithms and more recently deep learning. Broadly speaking, this approach attempts to mimic the process of natural learning whereby a person gradually develops certain knowledge and skills through continuous trial and error. Some key advantages of such an approach are overcoming the challenge for human programmers to develop multivariable algorithms for complex tasks (which they may not be able to do) and allowing for the greater versatility and agility of the algorithms.

As AI systems learn, they are able to approach or sometimes exceed human performance in particular areas. From transcribing handwritten texts, to recognizing objects and patterns in images, to providing complex predictive analysis, AI can take on a share of many "clever" tasks (that are often resource-intensive) and complete them at a fraction of the time and effort required by a human, especially if coupled with other technologies. For example, it can take several days for a human specialist to examine 1 400 acres of farmland on foot to identify areas where crops are insufficiently hydrated or fertilized. Instead, water and fertilizers are applied uniformly across the entire farmland at particular time intervals. Alternatively, an AI system can quickly identify areas that need water or fertilizers by analyzing real images of farmland taken by drones, allowing for targeted use of these resources.

AI's ability to perform intelligent tasks opens opportunities to improve current agricultural practices by: (i) providing support services previously deemed too resource-intensive, expensive, or unavailable (e.g. due to lack of skills and expertise among local professionals); and (ii) driving down current operational costs by saving time and labour performed by agriculture workers.

Increasingly today AI is considered one of the most potent solutions to the many challenges the agricultural sector faces in low- and high-income countries. Following the healthcare, automotive, manufacturing and finance sectors, AI has entered the agriculture domain and is providing cutting edge technology with applications throughout the food system including production, distribution, consumption and harvest yield uncertainty. AI-enabled technologies can help farmers improve crop yields, address the challenges of soil health and herbicide resistance and use resources more sustainably to reduce the agricultural sector's greenhouse gas emissions.

Areas of application

Some of the broad areas of AI application in agriculture include the following.[1]

- **Crop, soil, and livestock monitoring**. AI systems can support farmers in monitoring the condition of their crops, soil, and livestock and provide timely recommendations on particular actions and decisions. For example, by analyzing inputs from field sensors or studying images, AI algorithms can help determine the best time to sow seeds, collect fruits, spread fertilizers and/or provide specific treatment to cattle. They can also help detect which particular plants or animals require an intervention, thus allowing for more efficient use of resources.
- **Detection of pests and diseases**. AI systems can examine digital images taken by drones, agricultural robots, or farmers using a simple smart phone camera to detect pests and give concrete advice to agricultural workers on how to prevent their spread, treat affected plants or mitigate the damage caused. At the same time, AI can analyze data on the behaviour of livestock to detect abnormalities and identify potentially sick animals, thus allowing timely treatment.
- **Weather and temperature forecasting**. AI algorithms are able to assist with local weather and temperature forecasting using historical data and measurements made by local weather stations and field sensors. Better weather and temperature forecasting, can help framers to make better decisions on when to sow seeds, apply pesticides and plan for harvesting.
- **Predictive analytics**. By analyzing various field data and/or examining plant images, AI can generate accurate predictions about yields, and potentially, the quality of product. This can help farmers to project their revenues as well as make decisions on how much to sell and how much to save for personal consumption. AI systems can also be used to analyze consumption patterns to help predict demand for a particular agricultural product. These predictions can be communicated to producers to avoid any shortage or oversupply.

[1] All of the above applications of AI in agriculture are covered in the selection of case studies presented in this report.

- **Autonomous agricultural robots and farm equipment.** AI systems can be deployed on robotic platforms to direct and control their work performing assistive tasks, such as targeted irrigation, application of fertilizers and pesticides, collection of fruits and transporting equipment around a farm among others.

Areas of application are unlikely to remain static and as technology and user needs evolve, new applications may emerge, such as using AI to access finance and insurance for small-scale farmers. With AI-powered analytical tools, lenders can better evaluate credit risks and lend money more confidently to small farmers to help them expand production. (Cline, 2019) Combined with big data and improved connectivity (i.e. with the arrival of 5G), AI could also improve tracking of agricultural production to monitor product quality, enforce responsible conduct and practices and track food distribution and delivery.

Table 1. Selected examples of artificial intelligence applications

Application category	Artificial intelligence Application example
Agriculture robotics	• Start-up companies introduced robotic machines to control unwanted crops or weeds and help farmers raise volumes for picking or packing crops (Blue River Technology, United States of America) • Robots harvesting strawberries with a productivity of eight acres per robot per day representing the equivalent of 30 labourers (Harvest CROO Robotics)
Crop, soil, weather management and monitoring	• Deep learning based applications, such as Plantix, developed to identify potential defects and nutrient deficiencies in the soil including plant pests and diseases (PEAT, Germany) • Drone-based aerial imaging solutions to monitor crop health and precision-based chemical use deployed with a reported benefit of up to 80 percent reduction in pesticide used (SkySquirrel Technologies) • Applications that analyze agricultural data derived from images captured by satellites and drones to “detect diseases, pests, and poor plant nutrition on farms” (Farm Shots, United States of America) • In Andra Pradesh, India, up to 3 000 farmers received a Microsoft supplied AI-sowing app with advisory text messages over their phone, reporting yield gains from 10 to 30 percent

Application category	Artificial intelligence Application example
Predictive analytics	• Machine learning (ML) algorithms used in connection with satellites to predict the weather, analyze crop sustainability and evaluate farms for the presence of diseases and pests (Predictive Analytics, United States of America) • Ramos-Giraldo *et al.* (2020) developed a low cost automated drought detection system using computer vision through visual reading of leaf wilting status for corn and soybeans coupled with ML algorithms to document drought response in corn and soybean field crops. Using ML, the application predicts the drought status of crop plants with greater than 80 percent accuracy relative to expert-derived visual drought ratings.

AI in agriculture market

Analysts estimate AI in the agriculture market reached USD 1 billion in 2020 and is expected to grow to USD 4 billion by 2026. (Markets and Markets, 2020) There is an observable increase in investments in AI start-ups across all industries. (OECD, 2018). This is largely driven by the strong returns investors receive from AI capital allocations. (Loucka et al., 2019). Governments and public institutions also invest in AI-enabled solutions, due to its perceived strategic importance. So far, investment in AI for agriculture accounts for a moderate share of total AI investments. The interlinkages between different industries are likely to result in spillover effects, whereby an AI application developed for one industry can quickly make an impact on another. One such example is computer vision, which, while being an essential technology for autonomous driving, can also have a transformative impact on the agricultural sector.

Key factors affecting the use of AI in agriculture

The recent success of AI has been largely driven by progress in the following three areas. (ITU, 2018).

- Computing power and capacity: Processing units underwent tremendous improvements in the past decades, with new units being ten times faster than those used in the early 2010s. In addition, the emergence of cloud technology has delivered much cheaper computing and storage services on demand. All these advances enable development and deployment of complex AI algorithms that frequently rely on extensive processing capability that was once scarce and costly.
- Data: The capacity to capture, combine, store and access data has also expanded hugely. Digitization of many daily activities, continuous deployment of sensor networks, the rise of the Internet of Things and the Big Data all contribute to ever-growing volumes of information that can be used to train AI systems in increasingly diverse domains. International Data Corporation estimates there may be 163 zettabytes (one trillion gigabytes) of data by 2025, or ten times the data generated in 2016. (Gantz et al., 2017)
- Algorithms: The techniques and approaches for designing AI architecture and teaching AI algorithms have improved with advances in computer science and mathematics. The progress in the design of neural networks has led to the emergence of more accurate AI systems as well as the creation of models that learn quicker and require less training data. With more knowledge accumulated on algorithms and techniques, AI systems became more versatile and reliable, opening up routes for new applications.

Alongside the above drivers of AI technology, there is also a range of challenges to be considered when adopting AI solutions for agriculture.

- Information communication technologies (ICT) accessibility and infrastructure: As for any digital solution, AI deployment depends on the availability and functionality of ICT infrastructure in target areas and communities. While many operations can be completed with Cloud technology, connectivity remains essential for effective use of AI platforms. Whether a farmer uses an AI-powered app on their smartphone, or a system of interconnected devices collects and analyses real time data for crop monitoring, connectivity is essential. At the same time, many remote regions and communities in developing countries are deprived of broadband coverage, particularly in the Global South, where agriculture plays the most significant role. There are a range of initiatives to mitigate this barrier. Most recently, the Smart Villages project piloted in Niger aims to gradually bring improved connectivity to over 50 000 remote villages across the country. (ITU, 2020).
- Data availability: The foundation of any AI system is data. AI requires large sets of data collected over time for training, model testing and verification. Although cross-validation techniques can be used for training on limited size data sets, it is generally preferable to have a diverse pool of data to build functional, robust applications. A range of projects has emerged to facilitate the search for training data. One example is the project by Ocean protocol[2] which aims to facilitate collaboration with data owners. There are also commercial solutions, often challenging, such as the one offered by Anolytics[3] to source data sets that are large and comprehensive enough for training and to predict outcomes more accurately. Countries' data protection laws can hinder data collection, storage and evaluation but not always.
- Costs: Despite significant reduction in operational and data storage costs, deploying AI systems can be costly because of the high expense to develop and configure AI models and data acquisition. To mitigate this challenge, open source solutions are possible, including open or free datasets often provided by research institutions and specialized foundations.
- Ethical considerations: While AI systems boost efficiency and productivity, they can affect workers who may lose their jobs because of the higher cost of human labour as compared to AI applications. A 2017 report by McKinsey Global Institute concluded that up to 800 million jobs could be lost to AI by 2030. (Mckinsey Global, 2017). The impact of this trend on agriculture needs thorough consideration. On the one hand, AI solutions can help small-scale producers to grow, resulting in the creation of new jobs. On the other, the number of jobs created may be much smaller than those replaced. The skillsets required to perform new work will also be different. In addition, access to AI technology may not be equitable leading to wider gaps and inequalities between different agricultural producers.

[2] https://oceanprotocol.com/
[3] https://www.anolytics.ai/solutions/agriculture/

Implementing an AI solution for agriculture

As in the case of other technologies, determining how applicable an AI solution may be to a particular challenge involves identifying the use case, developing key governing principles (involving regulatory requirements, stakeholders, legal framework, how well it works alongside existing systems, scale and other key requirements) and then determining which technology or architecture will help address the challenges of that particular case. A review of already available and tested solutions is an important starting point, since in some settings solving the most pressing challenges may not require the use of AI due to the availability of a simpler, cheaper and less resource-intensive alternative. Under most circumstances, basic connectivity must often precede any complex interventions, since it is a prerequisite for the use of many digital platforms and will automatically provide access to a wide range of tools and services. In settings where digital infrastructure is very underdeveloped and internet connectivity is low, SMS-based services and the superior coverage of mobile networks could be leveraged to deliver advice and notifications to crop and cattle farmers. The primary focus should be on the tools and infrastructure that can support delivery of the most relevant services to the largest number of people at the lowest cost.

In that context, a careful needs assessment should pay close attention to user needs and local conditions. A user centric approach to solutions should address specific user needs at various levels of the agricultural value chain. That approach should consider such factors as digital literacy, attitudes towards technology and other relevant circumstances that might influence their use. As showcased in a number of case studies in this report, intended users often have limited proficiency in digital technology and devices and may also be biased against them. Addressing these challenges through an appropriate design and deployment strategy (e.g. by simplifying the tool interface and holding local community training and workshops) can greatly increase the uptake.

Interoperability and shared infrastructure are a priority. Certain equipment and infrastructure needed for an AI agriculture solution may also be useful for applications in other sectors. For example, an aerial imaging solution for monitoring crop fields could also be used for disaster preparedness and early warning. An app used to receive weather information can also deliver preventive healthcare (e.g. messages with nutrition and healthcare advice). By identifying multi-functionalities of a particular tool it may be possible to find other interested stakeholders and partners, thereby unlocking shared financing solutions, gaining greater community interest, receiving government support and avoiding effort duplication.

Engaging local stakeholders and developing partnerships is another critical requirement. From providing resources to promoting community engagement, local stakeholders can offer invaluable support to innovation implementers. Therefore, it is recommended to engage them early on in the process to receive their feedback and to look for synergies.

In addition to the above, developers and implementers should take into account the potentially negative consequences of wide-scale AI adoption among target communities and come up with solutions and strategies to mitigate any adverse effects. The impact of AI on local employment (including seasonal jobs) should be considered with priority for financially accessible AI solutions that complement rather than replace the work of human farmers. For example, offering farmers previously unavailable diagnostic and monitoring solutions to improve resource use efficiency and prevent crop losses by timely pest detection could substantially increase yields without threatening employment. Instead, such an AI application is more likely to create additional jobs as more workers will be needed to collect and transport greater quantities of crops.

Conclusion

AI technologies rely on automated systems, use of robots and drones and increased implementation of data generation through sensors and aerial images for crops and land use through deep learning technology. In the coming years, the application of machine learning in various agricultural practices is expected to rise substantially provided several challenges to its widespread deployment are resolved, especially among developing country farmers. They include the prohibitive costs of the technologies, lack of standardization, lack of AI awareness among farmers and limited availability of historical data. While the agricultural sector is likely to see further adoption of AI, it is important that farmers are equipped with up to date training to ensure technologies are used and continue to improve. Extensive testing and validation of emerging AI applications will be critical as environmental factors that cannot be controlled impact on agriculture, unlike other industries where risk is easier to model and predict.

AI technology has great potential and stakeholders must seek ways to leverage AI applications to support and improve agricultural practices. The latter is of utmost importance to overcome some of the world's most severe challenges and advance the global SDG agenda in a post-COVID-19 world. A variety of factors will influence the development and integration of AI solutions for agriculture: ICT infrastructure, market size, private and public investment, availability of human resources, aggregation of data, to name just a few. None of these factors are controlled by any single group of stakeholders, and therefore cross-sectoral and multifaceted support is required to ensure AI development and integration in agriculture take the correct path.

In particular, implementing AI solutions needs adequate due diligence and attentiveness to the ecosystems where they are deployed. Certain applications may not be sustainable in a given context due to resource and capacity limitations, in which case a simpler technology may be a better choice.

The key challenge is to ensure that AI applications in agriculture do not produce any significantly negative externalities and that their benefits are widely distributed and fairly shared among target communities.

Plantix - your crop doctor: every month around one million smallholder farmers use the Plantix app to grow healthier crops

Bianca Kummer, Karan Raut (Plantix) and Srikanth Rupavathara (ICRISAT)

FOCUS
The main function of Plantix is to assist farmers in automated detection of plant damage that occurs during crop production. The application is used in India and South Africa.

Context

The global challenge is well known: by 2050 the population needs to increase total food production by 70 percent. Smallholder farmers in developing and emerging countries, who presently produce 80 percent of food globally, have to almost double their production. The question is how we deal with this problem when many parts of the world are already struggling with a variety of problems such as population growth, increasing housing needs, diminishing agricultural land, desertification and climate change including its consequences (FAO, 2017).

Support and knowledge are probably key to increasing yields, but as smallholder farmers often live on the margins of society, it is difficult for them to have equal access to information and resources. One solution is to proactively strengthen the global farming community with timely, reliable and localized agricultural knowledge.

Physical agricultural extension systems in developing and emerging countries play a pivotal role in providing advice to farmers. However, there are few such systems compared to the large number of smallholder farmers. There are at least 570 million small and family farms (Lowder *et. al*., 2016) with an estimated 1 billion people working in agriculture, representing more than 28 percent of the global working population (Cassidy and Snyder, 2019). Plant damage from pests, diseases and nutrient deficiencies reduces crop yields by up to 30 percent, showing the need for extensive agricultural technology transfer and support. Also needed is comprehensive and timely information on innovative cultivation methods and the correct use of pesticides and fertilizers (Kumar *et al.*, 2020).

In the developing world there is tremendous pressure to reach out to farmers during the crop season, made all the more difficult by the remoteness of farms throughout rural areas (Salunkhe and Deshmush, 2012). For example, the ratio of Indian extension workers providing advisory services to farmers is very high, 1:2 000 in some states, making it difficult to deliver timely, quality services to those in remote areas (Rupavatharam *et al.*, 2017). Some reports suggest only 6.8 per cent of farmers in India have any access to extension services while women farmers have even less (GFRAS, 2012). There are many information and communication technology tools (ICT) available to support farmers but the vast majority do not offer customized options to address the real time problems they face during the farming season. Timely, specific advice is key to improve yields, lower production costs and reduce the impact of chemicals on both humans and the environment, to sustain livelihoods in the long run and make farming more profitable.

One such innovative effort by a German start-up company involved designing an application (app) called Plantix for android based smartphones with AI-backed solutions. The app provides instant information specific to individual growers and the crops they raise.

The main feature of Plantix is to help the farmer automatically detect plant damage that occurs during cultivation. The identification process determines plant diseases, pests and nutrient deficiencies and comes with necessary crop management advice including symptoms and triggers and the biological and chemical control measures to alleviate yield loss. The user uploads a picture of the plant damage which is further processed with the help of deep neural networks (DNN) using artificial intelligence (AI) and machine learning algorithms to identify the disease within seconds. Plantix also provides complementary features like crop specific farming practices, recommendations or direct linkage to quality inputs, to empower smallholder farmers with timely and science-backed advice that enhances crop productivity.

Methodology

In Hanover, Germany, the company ran an experiment in 2015 to automatically detect nutrient deficiencies in tomatoes using 200 tomato plants grown experimentally under deficient soil nutrient conditions. After demonstrating that AI is able to correctly identify damage under greenhouse conditions, based on a single picture, it was time to further elaborate the approach to meet field conditions and extend the database for the DNN training needed for these conditions. After visits to several different countries it became clear that India was the most suitable one to adapt the app to real time conditions in the field.

In 2015, India experienced high growth in mobile network services and significant improvements in its digital infrastructure. India's mobile data service cost is low (McCarthy, 2019) and has high penetration in rural areas. Hence, Plantix decided to focus first on Indian smallholder farmers who have greater access to smartphones. The company has since received support from its on-site partner, the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). During the 2016 crop seasons the focus was on 17 major crops. Thanks to ICRISAT's network connections with governmental and non-governmental structures it was possible to adapt and improve Plantix quickly for local crops in India.

The initial work of image sourcing, annotation and agricultural advice was critical, especially to build robust datasets to best train the DNNs. Scientific experts from Plantix and its partner institutions were instrumental in tagging the pictures to respective diseases through a cloud enabled database. Plantix was and is still demonstrated and tested through training for extension workers, agricultural officers from different government departments, students and staff of agricultural universities as well as farmers in a number of Indian districts. The ongoing discussions with these stakeholders and their feedback are needed to best lead and extend app features.

The automated image recognition feature health check is able to identify over 500 pests, diseases and nutrient deficiencies involving 50 crops with more than 85 percent accuracy. A recent internal field test of the Plantix app's performance found validation accuracy of 92 percent (sample size n = 383) detecting pests and diseases with training by AI experts. Backend algorithms are continuously improved by identifying performance from validation trials conducted in farmers' fields.

Other app features which contribute to the holistic needs of farming are the following.

a. A digital library: users can look up more than 700 types of plant damage, arranged according to crop and the respective growth phases in which they occur. The user receives important information at a glance, from the trigger for the disease to its prevention and biological and chemical control measures.

b. An interactive community: enables cross learning and discussions among all agricultural stakeholders. It is an interactive and global forum to share best practices and allows users to seek help from others on their problems. On an average day 15 000 posts are created and answered while 80 000 posts are opened and read.

c. Crop advisory: a prophylactic crop protection management system guiding farmers through the whole agricultural season based on their crop sowing date. Recommendations are available for multiple crops, covering topics like field preparation, sowing, irrigation, fertilization and crop protection measures.

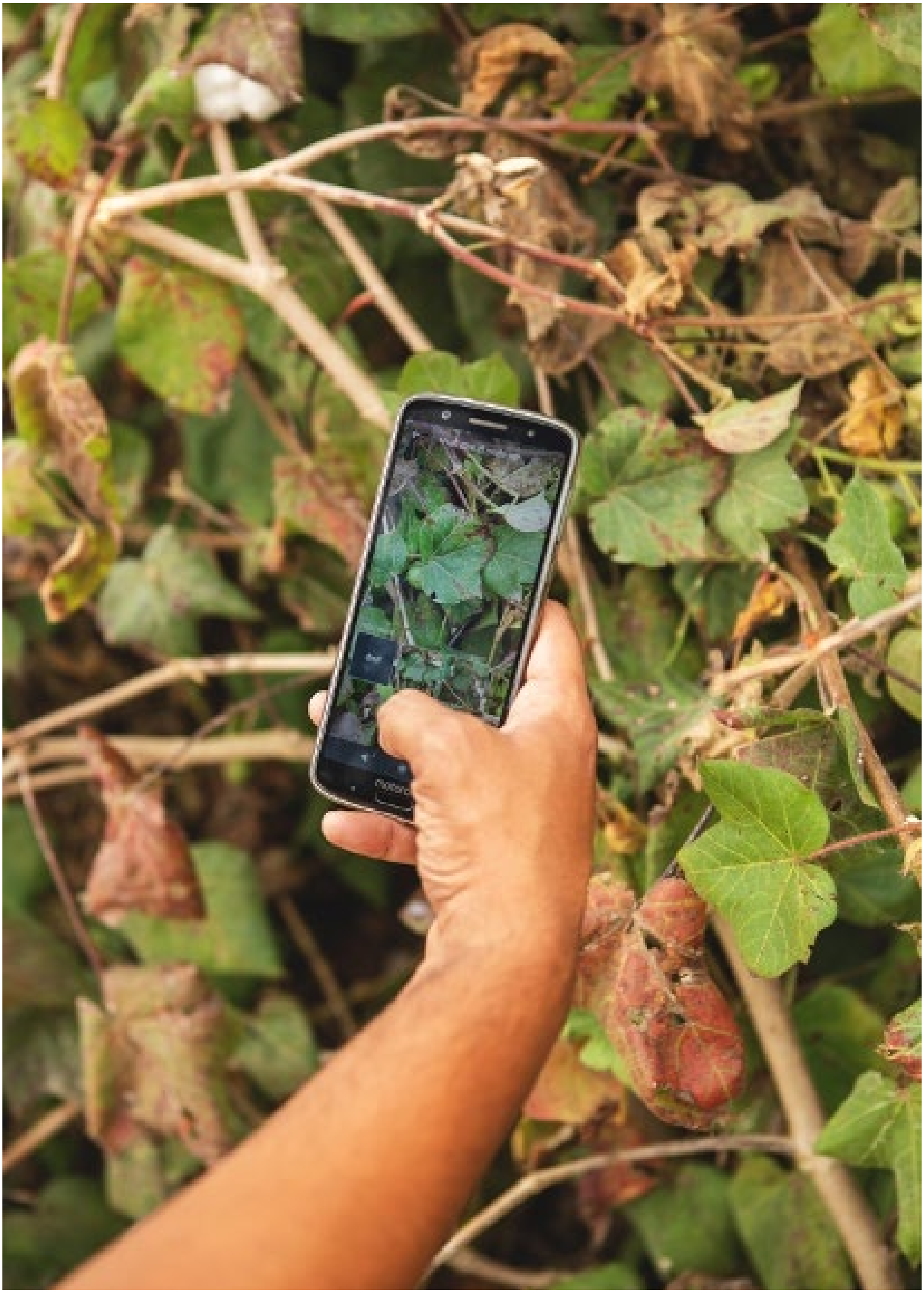
d. Fertilizer calculator: a tool to calculate seasonal fertilizer needs based on crop and plot size. The user can select from different recommended fertilizer combinations and receives advice on scheduling when and how much fertilizer to apply to their crop.

e. Automated disease alerts: data collected through Plantix images are tagged with geolocation and time. These data enable Plantix to warn farmers in real time about possible disease occurrence. On average, a farmer receives 1-2 disease alerts per month (during peak season) via push notifications that analyze diseases within a radius of 50 km.

f. Weather forecasting: critical for all agricultural related operations. Also includes automated advice on weeding, spraying and other agricultural actions and is applicable to the specific user based on their geolocation.

g. Retailer connection: the most recently launched Plantix feature that enables farmers to source the right product to address a particular problem. One of the most pressing issues is that around 50 percent of products purchased are unsuitable. By analyzing crop damage the app identifies the best product to treat it. Plantix uses this information to connect the user with a nearby preferred retailer to ensure access to the right product.

To assist as many farmers as possible, Plantix uses plain, intelligible language and is available in more than 17 local languages. Digital literacy is a key challenge and hence Plantix trained a team of experts who made field visits to better understand farmers' needs. User interfaces are redesigned and updated to improve and simplify use of Plantix, e.g. through comic icons. Such simple steps in the appearance and use of Plantix make it much more appealing to participating farmers.



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Impact

For a digital tool like Plantix, whose primary goal is to support thousands of farmers remotely, simultaneously and without any human on-site presence, it is difficult to present specific results from an impact assessment of actual yield increases or improved plant health, though there are numerous stories from users.

Data that are easy for a software company to monitor and measure are the number of user downloads, frequency of usage and feedback from individual users over time.

Shortly after the company was founded in November 2015, the number of app downloads stood at 10 000, the image database of plant damage was about 25 000 with automated image recognition for only a few nutrient deficiencies. Together with the support of its partners, within a few years Plantix has become one of the most succesful farmer apps, globally. Up to now the app has been downloaded well over 10 million times by users who have sent over 23 million images of their affected crops. Depending on the agricultural season, the app has about 1 million individual sessions per month, with around 80 percent of users from the current focus country, India. In Bangladesh, Pakistan, Brazil and Middle East and North Africa countries a high number of smallholder farmers with limited agricultural support also use Plantix.

The health check feature can now identify over 500 pests, diseases and nutrient deficiencies for over 50 crops with an accuracy greater than 85 percent. In the agricultural peak season users send between 60 000 to 80 000 pictures per day. The community feature registers significant activity: on an average day, 15 000 messages are sent, out of which approximately 8 000 are pure questions and farmers open and read about 80 000 posts daily.

The typical farmer does not need daily support, as agricultural problems are seasonal and do not occur every day. Accordingly, farmers use the app about a dozen times during one agricultural season, while the chances they will return to the app the following season are over 60 percent.

All these figures demonstrate on the one hand the pressing need for more agricultural support and on the other that digital solutions can make a substantial contribution to enhancing the productivity of smallholder farmers. These numbers are backed by real people and individual success stories, showing a glimpse of Plantix social media channels or in Google Play Store reviews. For example, the Facebook channel has 420 000 followers, videos on Youtube have been clicked up to 4.5 million times and over 47 000 users evaluated the app in the Play Store, where the average rating is 4.3 out of 5.

The following is a short excerpt of original quotes from user feedback received by Plantix.

“For healthy crops, we need disease free crops. Plants are often affected by disease. Early diagnosis of disease ensures healthier crop. It not only enables us to control the disease spread much before it inflicts damage to the plant beyond repair, it reduces the cost of maintenance of the plant and increases yield. Plantix is an easy and effective diagnostic tool in identifying and remedying plant disease well on time. I have been maintaining healthier crops ever since I started using PLANTIX APP.”

“It is a very informative app about agriculture and provides all relevant information about plant disease and pests. It is available in Urdu and easily understandable for our farmers. Being the worker of Plant Protection, I highly recommend this app to all agri-extension workers. I found shahzaib Kashan very helpful to farmers in community. Thank you for this amazing agri-app.”

“Previously I was unaware of this app. It is very useful for every farmer in this country. One can understand easily. Many farmers don’t know about this app. Very thankful to the Plantix. In India shopkeepers will guide the farmers regarding the usage of fertilisers and pesticides. Farmers will blindly follow them. Now everything changed. Everybody is learning easily through online. This app is very useful. Once again I want to thank you. Malla Reddy. Nellore. A.P.”

From the very beginning, the basis for improving the app and its agricultural advice are still closely linked to users’ activity. As every processed image is time and geo-location tagged, helping create a database with potential to generate a decision support system, Plantix can only improve, the more plant images it receives from users. The power of processed, anonymized and aggregated data not only impacts on individual users, e.g. for automated disease alerts, but can also significantly contribute to the overall agricultural ecosystem. So called agricultural ground-truth data from the masses is not available nor trackable in real time. By giving agricultural stakeholders like policymakers, researchers and non-governmental organizations (NGOs) access to processed and aggregated data, they gain important insights on how to improve policies, extension activities, research fields and programmes. Plantix has closely linked web applications to aggregate, filter and visualize its data in various ways related to time and space. This could help stakeholders identify areas at high risk of imminent food shortages, e.g. decisions based on serious plant disease infection in a region can be visualized so extension staff can alert nearby growing areas. So far, there has been limited evidence of other stakeholders in the agrisystem employing data driven decision-making. However, one important step in this direction occurred when Plantix, ICRISAT and the Centre for Agriculture and Bioscience International (CABI) launched the first real time tracking of invasive fall armyworm in India (live tracker). Plantix hopes that more pest tracking will follow in the future.

Innovation and success factors

The unique innovation of Plantix is its advanced technology with a high quality trained DNN that automates disease detection in real time situations. Development of an easy-to-use interface in multiple local languages and feedback loops from end users make the app a delightful experience for semi-literate farmers. Another success factor is accessing a digital application from any location, providing advice regardless of the time of day. From the advisory perspective the app is solution-oriented rather than simply informative for farmers.


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The most critical factor during the development of Plantix is the ongoing participation by important stakeholders in an agricultural ecosystem like ICRISAT, local government agriculture departments and universities as well as farmers who contribute to its evolution. Plantix has harvested the strengths of its partners to improve content for adaptation to local circumstances and effective dissemination of the app. This is a good example of a public-private partnership to support smallholder farmers in the agri-ecosystem. For example, Plantix was launched for the first time in the Telugu language by the Chief Minister of Andhra Pradesh at Vijayawada, India in May 2017. Local TV stations and social media covered the event extensively, leveraging the dissemination of Plantix through its network in the state. Another key factor is targeted crowd sourcing of plant damage symptoms, a good example of citizen science leveraging the collective wisdom of farmers, agricultural scientists, extension workers, policymakers and NGOs.

The most important external aspect was competitive pricing for mobile services with low priced data packages in emerging markets like India. This has led to higher smartphone penetration in the last five years and contributed to the exponential rise in the use of Plantix in rural locations. It is predicted the number of internet users in India, at present 560 million, is bound to rise and further the impact of remote digital tools to access knowledge and make their farming more profitable.

Constraints

The Plantix app can only be used by farmers who have at least occasional access to smartphones, e.g. on a household level and who have a certain degree of literacy as well as digital literacy. Even on a global scale the number of smartphone users (45 percent) compared to feature phone users (61.5 percent) is still slightly unbalanced. As mentioned, the target country, India, has low prices for mobile data (McCarthy, 2019) and around 36 percent of its over 1.3 billion inhabitants has a smartphone, one of the highest penetration figures among emerging and developing countries in the world (Statista, 2020). Digital participation by smallholder farmers is very likely to increase in the post-COVID-19 era as disruption to physical knowledge transfer in all sectors, including agriculture, can only be alleviated through digital platforms like Plantix.

Some constraints during implementation became opportunities to extend Plantix features. For example, during the initial phase, farmers' feedback highlighted the lack of weather information to indicate the best time for sowing, weeding, pesticide application and harvesting. The Plantix team quickly included and implemented a weather app to provide weather forecasts based on user location.

It became clear during the field visits that Plantix failed to identify many pests and diseases, leading to user dissatisfaction and farmers dropping out of the app. The team realised the importance of this constraint and this led to the ongoing improvement of the DNN, introducing a community feature to allow users post all their agricultural problems and discuss remedial measures with experts and fellow farmers in the community. Some disease symptoms are too developed to be managed after their appearance, causing yield losses to farmers. This was overcome by introducing advisory features which guide the farmer to grow healthy crops right through from sowing to harvesting.

A still unsolved issue is the lower participation of women and inadequate access to extension services. Women farmers make up nearly half the global agricultural labour force, but have even less access to extension services than men (Lamontagne-Godwin *et al.*, 2017). Although smartphones and digital tools are gender agnostic, Plantix estimated that about 90 percent of its users are male, most likely to do with decision-making and power in the agriculture sector.

While the targeted smallholder farmer normally cannot afford an Apple iOS device, Plantix has recently responded creatively to the request for using AI in iOS devices. Instead of creating an entire iOS platform software, the team took a novel approach that uses WhatsApp chatbot and made AI services available to all users irrespective of their smartphone software. This allows farmers to use Plantix at least some of the time without having to download the whole app.

A major challenge farmers faced around Plantix during implementation was that advice and recommendations on pest and disease management were not leading to easy access to products from a local trader. It is reported that a significant share (from 40 to 50percent) of products sold by local traders in India are not genuine (or are faulty), because retailers have knowledge gaps or increase profits by selling those products with higher margins (Federation of Indian Chambers of Commerce and Industry). Access to markets is a major constraint in emerging markets where the supply chains are opaque and disconnected to the needs of local farmers. Unlike fast moving commercial goods, the bulkiness of agro-inputs makes it harder to deliver them to remote locations because of increased transport costs. Naturally, farmers tend to use shops nearest their village, where some traders may entice them by offering easy credit but at very high interest rates or buy-back deals for their crops at harvest time.

Plantix has addressed this by providing farmers with advice on identified plant diseases and also market linkages by building the capacities of retailers in rural areas. Plantix set up a successful pilot in Telangana and Punjab to guide farmers in this. The approach has now expanded to more states to allow farmers request help from the app and receive guidance on the nearest retailer where they can buy recommended quality products. In addition, a partner app for retail shops converges requirements recommended by the Plantix app and its experts. Plantix has networked more than 10 000 retailers in the last six months.

The greatest external constraint is the current COVID-19 challenge, which not only leads to less private investment in all sectors but also limited availability of goods and services. The significant reduction in imported products, such as quality agricultural inputs, affects farmers and retailers in emerging and developing countries, while support from direct agricultural extension services has further declined. Scaling up digital ecosystems like Plantix could at least partly relieve the situation through remote advice. Unfortunately, global crises usually lead to a general slowdown within the investment industry, a situation also opposed by Plantix' internationalization plans. Plantix is confident that the post-COVID-19 situation will embrace a positive response to digital advisory tools and sustain smallholder livelihoods around the globe.

Lessons learned

a. Agriculture is practiced and managed in diverse ways which are very specific to the environment and their ecosystems. Having on-site partnerships with agricultural and horticultural experts in entomology, plant pathology, soil science and physiology is essential when making scientific-backed advisory content.
b. Know your target group as well as their pressing needs and focus on making your product user friendly for them with a strong focus on practical testing and feedback to create interfaces and features that are easy for end-users.
c. Reaching out to farmers in their local language is one of the most important aspects of communication and hence translating app content in easy but technically accurate language. Contextual relevance is integral to development.

Sustainability

The goal of Plantix is to encourage farmers to reduce their indiscriminate use of agro-inputs like fertilizers, pesticides and fungicides while achieving higher yields and healthier plants. Appropriate use of agro-inputs lowers production costs and increases productivity. This also reduces toxicity of agro-chemicals for humans, plants, soils and water bodies, thus making agriculture more environmentally sustainable. The increase in productivity and lower production costs make farming more profitable for smallholders. Plantix provides a universal tool to diagnose plant health automatically and deliver independent advice to the whole farm community. Existing farm extension services have more time to focus on advice which cannot be covered remotely or automated. Plantix empowers smallholder farmers by giving them a choice through accurate advisory services that empower the poor.

Replicability

Many agrotechnology apps have come on the market during the last three years and due to the range of pressing needs of the target group these efforts should be maintained. Plantix has successfully challenged and paired a holistic agricultural approach with a mature, automated and user friendly technology. This makes Plantix currently a widespread app among smallholder farmers across the world.

A small and passionate team of agricultural experts, software engineers, social scientists and research organisations have taken Plantix forward.

Instead of the pure replication of the app, which requires a lot of technical development time, there are two ways to scale the approach: expansion of the Plantix app to other locations in different climate zones or through the integration of its application programming interface (API) into third party applications that have already positioned themselves successfully in their respective markets.

In both cases, content needs to be adapted in advance to specific regions. This may be about plants and related diseases that are key in the region or language, culture and/or other specifics that need to be adapted in terms of image recognition, training, cultivation methods, product availability and user friendliness.

This requires strong local colleagues and partners as well as a high level of technical expertise to achieve effective and timely success.

Testimony

Farmer's name: Shivraj, Karnataka, Crop: maize. Shivraj is a smallholder farmer growing maize for the last ten years and every year pests and diseases diminish his yields and reduce his revenues. Like many other farmers, he depends on a local trader who prescribes and recommends agrochemicals against the pests and diseases affecting his crop. He used to spend up to 13-15 000 Indian Rupees (USD 170-200) per acre and despite this huge expenditure always ended with lower yields of 17-20 quintals (1.7-2 tonnes) per acre. Farming was not profitable because of low returns and heavy dependence on agrochemicals. In 2019 he heard about Plantix through social media and downloaded the app from Google Play Store. He started to use the crop doctor to diagnose symptoms of damage and followed the recommendations made by the expert advisory he received from Plantix. There was a dramatic reduction in spending on plant protection chemicals last season, down to 3 000-5 000 Indian Rupees (USD 39-66) per acre. There was a significant increase in crop yields which went up to 36 quintals (3.6 tonnes) per acre. He has now become an ambassador for Plantix, introducing it to many of his fellow farmers in his village.

Here is an extract from his original feedback.
"Due to various diseases and the destruction of insects, the drugs that they prescribed and delivered at the nearest drugstore could be very damaging. 13-15 000 Indian Rupees would have to be spent per acre and there would not have been much yield. All that was spent on about 17-20 quintals of maize per acre. Farming and yielding have not been successful for the last ten years. But with the advice of Plantix, I have been able to get 36 quintals of yield per acre at a cost of 3 000-5 000 Indian Rupees just to surprise ourselves in the 2019-20 crop. Thank you from this little farmer."[4]

[4] Links and sources: https://plantix.net/en; https://blog.plantwise.org/2020/06/19/teaching-an-app-to-help-farmers/; https://yourstory.com/2020/04/startup-plantix-farmers-retail-inputs-crop-health; https://www.bbc.com/news/business-41580890; https://www.scidev.net/global/agriculture/feature/tailored-targeted-ai-apps-pave-way-for-smart-farming.html; https://www.youtube.com/channel/UCr2eDB6CRRS5Z9Yec646tMg/videos

AI based early warning system for pest management

Dhruvin Vora and Rajesh Jain, Wadhwani AI

FOCUS
The smartphone app described in this chapter helps farmers detect and monitor the progress of pests and provides recommendations to farmers on the best time to apply pest controls. The app reduces time delays between monitoring, pest detection and provision of recommendations and is widely applied in India in cotton farming.

Context

Nearly 29 million farmers across the globe rely on cotton farming for their livelihood, a majority of whom are smallholder farmers. Ten million of these farmers reside in India. (International Cotton Advisory Committee's Cotton Data Book, 2020) For these farmers, pest infestation is a significant challenge, which leads not only to crop loss and reduced incomes, but can push farmers already fighting poverty into despair and often suicide. Bollworm infestation is also sharply on the rise in regions where it was hitherto under control. For example, a widespread infestation of 40-95 percent due to pink bollworm was detected in b t cotton in Maharashtra in June 2019, which accounts for an anticipated yield loss of 20-30 percent from pink bollworm.

The pests lay eggs that are difficult to detect and within a few days develop into larvae that make their way into the cotton boll, doing irreparable damage to the crop. Knowing how much pesticide to spray and when is not an easy decision for farmers. Applying too soon can kill pests that are beneficial to a field's ecosystem and spraying too late could be wasted effort, as pest growth can exceed a level that is economically sensible to address.

The Government of India tries to implement integrated pest management (IPM), a scientific and holistic way of pest management, among smallholder farms through the state's agriculture extension programme. This involves extension workers, both from government and private programmes, monitoring a set of sample farms in a village and entering pest data into a centralised system. The data are then analyzed centrally and a generic pest management recommendation is provided to all farmers in the region. The extension programme has been unsuccessful in implementing IPM due to several practical challenges: i) error-prone counting of pest density; ii) delay in raising alerts and providing advisory due to manual data entry; iii) low skilled workforce vis-à-vis the knowledge required by IPM; and iv) lack of adequate staff.

Methodology

In response to the above challenge, the company Wadhawani AI has developed an object detection model that identifies and counts pests in a trap using images taken by farmers and extension workers. The model is deployed on the ground via a smartphone app that a farmer with low digital literacy can use. The model runs with the phone off line, which means it can operate even in remote locations where there is no network. Based on the pest density and the action threshold defined by an agricultural scientist: a) real time alerts are generated; b) recommendation (advisory) on the right action to be taken is provided, in case the pest density is above the economic threshold limit (ETL).

Based on the count of identified pests and the action threshold defined by an agricultural scientist, the farmer receives real time recommendations on the right course of action to save their crop from avoidable losses.

Impact

Our solution is currently deployed in western and southern India and we are in the process of conducting field trials, user randomised control trials and controlled environment studies to establish the adoption and impact of the pest management tool. Some preliminary experiments in Karnataka in the summer indicated that our solution could lead to revenue gains of as much as 24 percent.

So far, we have received positive feedback from many users.

“I use the pest management app regularly (twice in a week) and I do this to get more yield. When I received a recommendation to spray, I followed it and sprayed on my farm. I knew it was working when I saw the upper leaves looked healthier when compared to the lower leaves”. Lead farmer from Medleri, Haveri District

“I could see the leaves curl and when I checked on the app, I received a recommendation to spray. As soon as I received it, I took a screenshot [of the app] and showed it to my local pesticide shop owner. I asked him to give me these exact chemicals only and no other chemicals. I have had bad experiences with chemicals before, but this time I think I got good results from spraying.” Lead farmer from Timmapur, Haveri District

Innovation and success factors

With the use of AI (artificial intelligence), we are able to provide farmers with real time recommendations thus reducing the time it takes to reach out to experts, allowing them to take timely, appropriate action to protect their crops from avoidable loss.

Some of the factors that have helped us deliver success in terms of the deployment approach are: a) deployment through existing programmes, focusing on those that are well run as early adaptors; and b) having a user centric approach to developing a solution. These are detailed in the lessons learned section.

Constraints and lessons learned

Here are some of the things learned from field trials and implementing our solution.

1) **Focus on private (non-governmental) programmes as early adopters:** We established a partnership with the Better Cotton Initiative (BCI), a collection of non-profits that promotes better standards in cotton farming and practices across 21 countries and accounts for over 19 percent of the cotton grown worldwide. We have similar partnerships with the Government of Maharashtra.

   Last year, we conducted field trials with Welspun, one of the major BCI partners in India and with PoCRA, a World Bank funded Government of Maharashtra programme also part of the trial. However, it was observed that the private (non-government) programmes are more structured with better adoption of new technology and adherence to defined protocol. As a result, the workflows of private programmes are easier to integrate and iterate. It is also clear that government programmes, though larger in scale, do follow new practices. Our strategy is to focus on private programmes as the primary, early channel of scaling and use that as an example for government programmes to follow.

2) **Human centric design:** As we ran our field trials, we updated multiple aspects of our solution to address usability issues for the beneficiaries.

   2.1) **Improvements to address limited digital literacy:** The end users for the pest management app are smallholder farmers. Typical users come with varying levels of digital literacy and ease with smartphones. Further, their literacy level can be multifaceted, not necessarily binary or even scalable. In the series of usability tests conducted for our prototypes, we found users struggling with elements such as drop downs and next buttons. To make the app interface easy to use, we built image and voice interfaces including features such as voice-based navigation assistance in local languages.

   2.2) **Phone set up to work offline to address limited network connectivity:** The settings in which these solutions are deployed are typical of large urban centres. Internet connectivity can be unreliable, particularly on remote farms, and this leads to very high latency when uploading the trap image, over two minutes in many cases. To overcome this challenge, we compressed the size and computational requirements of our detection models by over 100x (the model size is below 1MB) to deploy them easily on the phone. The inference (pest detection) can now run without network connectivity.

Recommendations for other ICT (information communication technology) solutions

- While working with smallholder farmers, ensure you have a good understanding of the digital literacy levels of the end-users and design for that level. Image heavy and voice-based interfaces are better for users with low digital literacy.
- Ensure your designs cater to low resource settings and plan to address challenges such as low network connectivity.
- Well run private programmes are great partners to start the deployment and to demonstrate the possibility of early success.

Sustainability

We are a not-for-profit organization and provide this technology to farmers for free. Our founder donors, Dr Romesh Wadhwani and Sunil Wadhwani, fund the work of the organization. In addition, the work is also funded by Google.org under the AI for social good initiative. Various funding agencies (including government) have expressed an interest in continuing to finance this initiative as we scale up the programme.

With the use of this technology it is expected farmers will reduce their current use of pesticides and improve their yield through timely and optimal usage of those pesticides, leading to many environmental and health benefits.

Replicability

The use of AI makes this practice scalable in various contexts. With the algorithm doing the pest identification and providing recommendations, the solution can be scaled up to multiple geographies and thousands of farmers without the need to add experts or employ additional manpower.

We already have plans to scale up this technology to multiple cotton growing regions in India and other developing countries through our partners. BCI is one of our close partners and the International Cotton Advisory Committee (ICAC), a technical advisory body to the governments of 29 major cotton growing member nations, is another partner.

Testimonies

“This solution will help both the farmers as well as our teams with early detection of bollworms and teams will ensure that the farmers take necessary action in the given short window so that we are able to help them to save their crop and also that this will stop indiscriminate use of pesticides which happens either due to calendar spray or due to the panic created amongst farmers , when they see the attack. Solutions like this will help us scale our operations to more geographies and larger numbers of farmers with limited field resources.” Mr Vivek Pawar, CEO of Deshpande Foundation

“This solution will help us better monitor our farmers spread over wide geographies and also the teams to better advise and take field visits to the infected farms and villages.” Mahesh Ramakrishanan, Vice-President Welspun, Sustainable Cotton Initiative

“This solution will not only help farmers but will greatly help our core team to monitor remotely as well as ease out the pressure on the extension workforce.” Chandramohan Bund, Manager Welspun, Wardha

Farmers speak

“In farming we have to make the right decision at the right time. We often face the problem of pests and diseases which adversely impact our yield. Though remedial measures are available, we don’t have diagnostic tools to identify pests and disease. The cost of control be it biological/chemical measures is prohibitively expensive. There is no way we can predict the likelihood of such an attack. Either we make a wrong diagnosis or misunderstand the signal. The symptoms shown by the leaves could deceive even the trained eye of an expert. In India there is a mismatch between extension workers and farmers (ratio of extension staff and farmers). This is where the mobile app comes in handy as a diagnostic tool for the farmers. It provides a solution instantaneously. No need to wait for days to get plant advisory.” VKV Ravichandran, Lead Farmer, Nannilam village, Tamil Nadu, India Board Member, Global Farmer Network

“When I was spraying on my farm, my neighbours [neighbouring farmers] saw me. They asked the reason for spraying and the name of the pesticide. I told them about the app and the recommendations that I received. They were curious to understand - how can I believe in a phone and I showed them how it works (showed them the app and the process of getting results). After I finished my demonstration, they were convinced and some of them are planning to take a similar spray as well.” Lead farmer from Ankasapur, Haveri District

PlantVillage Nuru: smallholder farmers in Kenya see income boosts with their personal AI assistant

David Hughes, Annalyse Kehs and Pete McClosey (Penn State University)
and Moi University

FOCUS
Initially developed for education and awareness raising, the solution is now used by farmers to find and cultivate healthy plants in farms affected by pests. It is used in Kenya in cassava farming.

Context

Josephine Arisat from Asing'e location in Busia County has been growing cassava since 1995. Climate change is a major challenge for smallholder farmers such as her. Cassava is being promoted as an important adaptation to climate change as it can withstand periods of drought which are becoming increasingly frequent and significantly affect other staples like maize.

But major constraints to cassava production across East Africa are viral diseases: "Initially, I was planting cassava for subsistence purposes in a two-acre piece of land since there were few cassava diseases at that time". But when she had a commercial opportunity after 2016 to sell her cassava she had to shift to planting only half an acre because the threat of disease was too great.

The first problem Josephine faced was transitioning from subsistence to commercial cassava production. Her yields were kept low from the chronic infection of her cassava by two viral diseases: cassava mosaic disease (CMD) and cassava brown streak disease (CBSD). These diseases massively reduce yield and are transmitted from one season to another as farmers plant infected cuttings taken from mature infected plants. Whitefly also transmits these diseases. In one study in the Democratic Republic of Congo planting of cassava infected by CMD reduced the yield by between 77 and 97 percent. When PlantVillage arrived in Busia and met Josephine her situation was very similar to other farmers we worked with in Tanzania and Kenya where less than 10 percent could accurately diagnose diseases in their cassava fields.

The knowledge required to diagnose the problem was not reaching farmers like Josephine. Normally it came from extension services but they are understaffed and under-resourced. Farmers simply did not have access to expert advice.

Methodology

PlantVillage gave Josephine a smartphone with the AI assistant, Nuru (artificial intelligence), which can diagnose cassava diseases as well as a human expert can. In early trials in Tanzania we found the AI assistant was twice as capable as extension workers. The app was co-developed with cassava diseases experts at the International Institute for Tropical Agriculture (IITA), notably Dr James Legg, and smallholder farmers and built by PlantVillage at Pennsylvania State University. It was designed to diagnose crop diseases offline so could be used in a typical Kenya field where no internet was available. The smartphone runs a convolutional neural network that accurately diagnoses cassava diseases using computer vision via TensorFlow, an open source machine learning platform developed by Google. A farmer like Josephine can simply hold the phone over the leaf and follow the instructions to receive an accurate diagnosis. You can see this in a popular video which Google made of our work.

Nuru is Swahili for light and the idea is that this personal AI assistant helps Josephine see the problem, namely that her fields were infected. But then we discovered a second, more serious problem: Josephine could not source clean seeds. Cassava is clonally propagated and the seeds are actually stem cuttings from a mature plant. If that mature plant is infected then the seeds of the plant will be infected too. Since healthy plants produce healthy tubers the lack of healthy seeds affected Josephine's income. Access to healthy seeds/cuttings was extremely limited, with an unregulated structure to verify quality. Because the clean seed system is still at an early stage in Kenya, Josephine had to find a new source of clean cassava cuttings and indeed she did. The solution to problem two turned out to be the same as that for problem one: use the AI assistant Nuru.

Impact

Josephine scanned her field for diseases with her AI assistant, Nuru using the PlantVillage app. Throughout late December she went through her field checking the health status of her plants. At the time she had no credit on her phone but since PlantVillage works offline she did not need it. When we provided credit in January, we received a flood of alerts on her activity as all her surveys were uploaded to the PlantVillage dashboard. It showed that on 19 December she used PlantVillage Nuru 32 times, mostly finding healthy plants as opposed to diseased ones. We were very confused. Why so much attention to healthy plants? Did Josephine not understand the purpose was to diagnose infection? On 21 March 2019 we visited her farm and discovered the fruits of her labour: she had a field full of healthy cassava plants. But how did she do it without access to clean seed?

What Josephine had done was turn the education tool we gave her into one to achieve a greater yield. Josephine used PlantVillage's AI system to choose only healthy plants from which she would take the cuttings for her new crop. In this way, she avoided starting off with high levels of the virus in her field. The critical aspect of this is that Josephine took a tool intended for one specific task and then invented a new use for it. We now teach this use to thousands of farmers in her county.

She went from a farmer not recognizing diseases in her field to one who could easily spot them on her farm and on other farms, applying the knowledge she acquired from the PlantVillage app. Since our AI tool works offline and in front of the farmer's eyes, she was able to learn about the different diseases at her own pace. After all, we believe in AI redundancy, not AI dependency. We know that the best neural network on the farm is the one in the farmer's head!

This is how Josephine describes the benefits of using Nuru. “Since I received a smartphone with the PlantVillage Nuru App, my cassava farming has improved. The smartphone application has helped me to identify cassava diseases and to know the different types of diseases affecting my cassava. Initially, I used to harvest rotten cassava tubers whereas their leaves looked healthy. I never knew that cassava leaves can showcase diseases. With the help of Nuru, I can scan my cassava leaves and know if they are affected by either cassava mosaic disease, cassava green mite or cassava brown streak disease. The phone also provides solutions to these diseases.”

At the start of 2020 Josephine was ready to harvest her field. It was not only special to Josephine, but extremely special to PlantVillage as it was truly our first field and the first farmer that PlantVillage has had an impact on from the start of planting to the end of the harvest. In the middle of March, 12 of our members joined Josephine to help harvest and weigh each of the tubers from the whole field. Three days later when it was all completed the results were, to put it simply, mind-blowing.

Out of 3 053 plants surveyed over 8 700 tubers were collected with a combined weight of 3 110 kg. The average tuber weight was 0.397 kg and the average weight of tubers/plant was 1.13 kg. The maximum number of tubers per plant was 13 and the maximum individual tuber weight was 4 kg. On average, there was a 126 percent increase in Josephine’s yield compared to previous years.

There were a total of 40 plants that were diseased (CBSD), approximately 1.13 percent of her plants. This is incredible as her neighbour’s field was rampant with disease.

Josephine thus had many more tubers to sell. However, there was an additional revenue stream available also. Since Josephine had a field of mature, healthy cassava she could establish herself as a seed entrepreneur and sell seeds to her neighbours.

So, overall, how much money did Josephine make? She was able to harvest 11 bags of cuttings from her field, each bag having 1 000 cuttings. Each bag cost approximately USD 10 (KSH 1 000) so Josephine made USD 110 (KSH 11 000) from this harvest. The cost is USD 0.05 per kg of tubers with the total amount of tubers being 3 110.9 kg and the average plant tuber weight 1.13 kg, the total amount Josephine can make is USD 175.89 (KSH 17 589). Without the app, assuming an average plant tuber weight of 0.5 kg, her total would be USD 77.77(KSH 7,777). This is a 55 percent increase in her income.

With her new knowledge Josephine has gone on to become a cassava tuber aggregator, collecting tubers from her neighbours’ farms to process before sending them to the aggregation points. This increases her profits even more.

Josephine still faces many issues: moles, waterlogged areas rotting tubers and theft but she is happy with her new skills and has seen the “light” that many other farmers experience using PlantVillage Nuru. It shows that AI can have tremendous immediate benefits for farmers. But the greater lesson is empowerment. Providing such tools can empower smallholder women farmers like Josephine to invent new models.

Innovation and success factors

The extension of science-based agricultural knowledge has always had a transformative effect on smallholder farmers. This was true following the development of the first extension system in Dublin in 1847 in response to the Irish Potato Famine. It was true of the transformation of American smallholder farming into the juggernaut of agricultural productivity in the 20th century via the extension systems of the Land Grant Schools. And via the same Land Grant system global sharing of knowledge occurs through the Green Revolution and the work of Norman Borlaug and others. But it is widely recognized, such extension systems have not had the intended impact they could have had in Africa.

The lesson from Josephine's use of PlantVillage is that expert level systems can run as AI software on a phone. The computing power of the standard smartphone combined with cloud computing resources to teach machines human level skills such as disease diagnosis place the power of AI in the palm of her hand. This is an expertise she can draw on anytime and through repeated use come up with a wholly new model of sourcing clean planting material.

The innovation and success can be attributed to the combination of three complementary factors: the modern smartphone, the cloud computing environment that facilitates learning by machines and the intelligence of African smallholder farmers.

Constraints

- Poor network
  While the app runs offline, areas with poor network make it difficult to update it when required and to send surveys to the PlantVillage database. We log all these surveys so experts can verify and validate the diagnosis given by Nuru. This is an issue PlantVillage continuously faces and we deal with it by gathering farmers in groups where there is network. These days are paired with training or workshops to learn about new app features or agricultural training so there is an incentive for farmers other than updating and fixing technical issues.
- Data bundles
  PlantVillage delivers data bundles to farmers so they can keep the Nuru application up to date, send surveys and receive feedback. Delivering the data bundles to 100 farmers has brought many challenges ranging from not knowing when they need data to monitoring their use of the data. The other issue is that some farmers use the data bundles very quickly because they use the phone often while others use the app more sparingly and have a resource of data. These challenges were addressed by testing how much data are required to upload the different surveys in locations with varying network speeds. Once we had an approximate number, it was applied to each farmer on our database so we could keep track of how much data they were using. Once they came close to their allotted amount, they were contacted to check the amount and delivered data if necessary.
- Charging phones
  One of the challenges we faced was how farmers could charge their phones. With 100 percent of our farmers on less than USD 2.50 a day, they did not have electricity to charge phones. This was solved in two ways. Some farmers take their phone to a charging café, where they check it in and have it charged for a certain period and then pick it up. There is however the risk of phones being stolen, we have had one

case. The other option is to buy a solar panel system to charge your phone, costing approximately USD 9.99 (KSH 999KSH) and available locally.

- **Lack of cassava market**
  The lack of a cassava market has been a problem since a CMD pandemic in Kenya in the 1990s. Since then, farmers have moved away from planting cassava to focus on maize. With families no longer choosing to plant cassava, maize is a household staple in western Kenya. PlantVillage has been gradually penetrating the cassava market by linking seed suppliers with farmers who are interested in growing cassava again, as it is a drought-tolerant crop and appropriate for climate change adaptation. After setting up 80 demo plots of clean cassava cuttings with smallholder farmers, there has been a significant increase in demand for clean cuttings from neighbours and farmers who saw the clean fields and were impressed. All the demo plots have a long list of farmers willing to purchase clean cuttings once the cassava is harvested.
- **Lack of disease knowledge from an under-resourced extension service**
  A major issue when interacting with any new farmer is their lack of education around disease prevention and treatment. PlantVillage hears two different objections: the cassava leaves are supposed to be yellow (they are not, they should be green) or the disease comes from the rain and goes away when the sun comes out (this is because heavy rain flattens the diseased leaves). Both explanations are incorrect and PlantVillage takes time to educate farmers through repeated interactions on what the diseases are and what to do about them. Beginning with farmer field schools and training, the Nuru application continues education offline.

Lessons learned

The main lesson we learned was that not only could smallholder, older women farmers (45-65 years old) use advanced AI first technology but they could invent new uses for such technology. These new uses led to significant financial gains in a single season.

This was an exciting lesson to learn as the AI tool is software and the marginal cost of adding new users to software is minimal, meaning we could expand the number of smallholder farmers using such advanced AI first tools with little additional cost.

From being on the spot, we learned you can travel to almost any cassava or maize field and expect to find either disease or pests. For maize, we most frequently found maize lethal necrosis disease (MLND), striga weed, or fall armyworm (FAW). For cassava, we found CMD, CBSD and green mites.

Another lesson learned specific to the Nuru application was that farmers really enjoy being able to see how the screen graphics show the disease in real time on their own crop fields. This was a critical component to their continuing education in diseases. Developing the app was a long process of co-creation with the farmers. They dictated how the majority of its features should be presented and what information received was most helpful to them.

In all sectors of society, we have seen how technology has led to transformative change by leapfrogging traditional barriers. This case study by PlantVillage has shown how AI first tools can be such drivers of change in communities of older, women farmers who grow staple crops like cassava.

Sustainability

The app is co-developed with farmers and runs offline to ensure we have the widest reach from subsistence to commercial farmers. Our approach to delivering smartphones to a group of farmers is not sustainable as there is great reluctance from the global community to donate smartphones, even for an emergency. PlantVillage argues that data and knowledge for growing your own food, in an unprecedented time of accelerating climate shock anomalies, should be free to access.

The cost of one smartphone for a farmer is around USD 150. Spread out across 30 farmers in a community (USD 5/person) over the lifetime of a phone (two years) means that it costs USD 2.50/person/year, excluding data costs. Thus it costs PlantVillage USD 2.50/person/year to provide normally unobtainable, proactive climate change adaptation advice and recommendations based on predictions and projections from the global expert community.

Examples of beneficiaries

Helen Barasa

Helen Barasa is a cassava agripreneur from Kajoro village, Nambale in Busia County. She started cassava production in 2000 and has since diversified to other crops like maize, soya and sweet potato.

Over the years, organizations such as the Ministry of Agriculture, the NGO ARDAP, and PlantVillage have helped her shift from agriculture to agribusiness.

© PennUni

Helen's farm has created great interest from farmers and organizations wanting to hold field days and on-farm training sessions. Ugunja Cassava Resource Centre (UCRC) held several field days at her farm and UCRC officers invited county officials from the Ministry of Agriculture to attend the sessions. Helen's 0.25 acre cassava plot shows remarkable growth without any cassava disease.

Helen obtained her NASE14 cuttings from a PlantVillage cassava seed entrepreneur and is expecting increased yields this harvest. Other farmers have begun booking cuttings from her once she starts harvesting.

Helen is spreading her success by training other farmers in her group on the importance of planting clean cuttings to increase yields.

''Sometimes, I get calls to go and help other farmers select clean cuttings using the PlantVillage Nuru application on my phone.''

Joseph Khaleke

Joseph Khaleke is a PlantVillage farmer from Kitale County, Kesogon village whose goal is to have a sustainable and well balanced food source from his farm by 2021. Joseph grows varieties of crops including different fruits. Currently his farm has bananas, millet, passion fruits and sweet potatoes propagated for commercial purposes.

Joseph's yields have increased by accessing free farming knowledge from PlantVillage. He now supplies healthy bananas to hotels in Kitale and delivers his millet to nearby schools. Joseph is also a seed seller as he plants quality seed.

How did you join PlantVillage?

I first learned about PlantVillage from Facebook early this year and joined their WhatsApp channel to interact closely with other farmers.

I then learnt of PlantVillage's free SMS Service and joined the SMS platform by sending my questions to 20307. This has been helpful as I receive farming tips and expert answers to my questions for free.

What problems did you have as a farmer?

Pests and diseases are a major problem. I was not able to identify the pest and disease affecting my bananas or the control measures to curb them.

Also, I have experienced problems with the soil. For instance, pests hiding in the soil which destroy the roots causing my crops to wilt.

How have PlantVillage services helped you?

Being part of PlantVillage, I have expanded my farming knowledge. Through being part of these platforms, I have learned about the type of fertilizer to top dress banana and the type of pesticide to spray on fruits. I shared my crop pictures through a WhatsApp channel and was advised on how to treat my affected passion fruits. Right now, my passion fruit tree has more fruits.

Also, I have learned about soil management practices whereby I no longer use lots of chemicals in my soil.

PlantVillage has remembered most farmers with feature phones so they can now access free agricultural knowledge.

Connecterra: predictive AI tools for early detection of disease - healthy cows for a sustainable dairy sector

Irina Bobicev and Emmy Koeleman, Connecterra

FOCUS
The solution uses sensors, cloud computing, and AI for monitoring the behaviour of cows to identify signs of disorders. The solution has been successfully used in Netherlands.

Context

World population will grow to an estimated 9.7 billion by 2050. This is over 3.5 billion more than the global head count in the year 2000. This spike in population growth in the coming years is directly related to increased consumption of food, spiralling into a global food gap of 70 percent by 2050, according to the World Resources Institute. Animal protein is an important part of a nutritious diet. The dairy sector is seen as an important contributor that can supply enough high quality animal protein, as well as provide employment opportunities and a way to boost local economies in the developing world. The dairy market is expected to continue to grow in the long term, with an expected increase of 35-43 percent. According to Rabobank (Dairy Quarterly Q2, 2020), milk production is forecast to continue expanding across dairy-exporting regions, despite weather-related issues, lower milk prices, and efforts to bring supply back in balance with demand in many areas due to COVID-19. The increased milk production will, however, come from fewer but larger farms in 2030. This indicates the ongoing consolidation process as fewer farms produce more milk. As the dairy sector becomes more consolidated and farms bigger and more professional the tools and requirements of farmers and suppliers will change as well.

Adding more cows to the already over 373 million cows grazing this planet, will not be a sustainable option to feed the world. Increasing farm efficiency, and actively working towards a net negative carbon effect of dairy farming is the only way to go.

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Picture 1. As technology and digitization on dairy farms take flight, this can make farms more efficient, productive and sustainable

Weaknesses of food system in focus

Dairy farming is a market ripe for disruption. According to a 2017 McKinsey and Harvard study, agriculture is the least digitized of all industries. At the same time, the challenges in dairy farming are greater than ever. Farmers are under tremendous pressure on multiple fronts and need the help of advanced technologies to make the transition. There is not enough skilled labour on farms and farmers are constantly dealing with market and milk price volatility. Therefore, decisions must be measured and well thought out. To take farming to the next level, digitization in agriculture is crucial. In dairy farming, we have seen some significant technology milestones, starting off with automatic milking systems at the beginning of the 90s to automatic feeding robots and sensor technology in the last decade. The innovation in hardware farm technology continues, but we see a shift towards more digitization tools and products around data, AI (artificial intelligence) and connectivity. Especially in the first quarters of 2020, there has been a rapid digital transformation in the global agricultural sector because of COVID-19. Farmers and other key industry players are more acutely aware of the need for sustainable and efficient farming practices and the weaknesses in our food system that is disconnected and faces threats from climate change and a dwindling labour force.

Applying AI in agriculture (methodology)

Of the many technologies being explored in agriculture, AI is seen as one of the most powerful and promising tools for farmers and agriculture. Farmers use historical data to their benefit, with data in large quantities, rich in variety and collected and processed in ever increasing speeds. Currently, the most popular applications of AI in agriculture appear to fall into three major categories: 1) robotics; 2) crop and soil monitoring; and 3) predictive analytics. The latter is of interest when dealing with livestock. Being able to make better predictions on what will happen, for example, enables farmers to proactively respond to the weather and prevent animal diseases. This can boost economic performance and unnecessary losses.

Applying AI in agriculture is, however, challenging because it means you must optimize the external, living world. That is different than, for example, using AI to automatically translate text into another language or play online chess. AI for agriculture means dealing with animals and farmers, each farm being different and unique, depending on where it is and the aim of its farm management approach. Each farm is an ecosystem on its own, experiencing a lot of unpredicted circumstances. And yet, all these unpredicted elements of nature and living animals are perfect for applying AI.

Machine learning for behavioural classification (methodology)

One of the main drivers of an efficient, productive and sustainable farm is animal health. Healthy cows become pregnant more easily, produce more milk and are less prone to diseases such as ketosis, mastitis and lameness. Wageningen University in the Netherlands calculated that mastitis (udder infection) costs a farmer EUR 240 per lactating cow per year and can result in a loss of 336 kg of milk (van Soest *et al.*, 2016). Canadian research showed that lame cows produce around 1.7 kg less milk per day (King, 2017). Behavioural patterns are key for breeding and animal health management. When a cow is in heat (fertile, ready to breed), she will walk more than normal and/or eat less. When an animal is sick, she might walk less and will stop ruminating. Animal behavioural patterns are therefore directly linked to the profitability of the farm. What if we can devise an AI system to learn behavioural insights and turn these data into actionable advice and interventions for the farmer?

Most of the cow behaviourial data available concern walking, derived from simple pedometers used to detect heat patterns in cows. Since 2013 Connecterra has been investing in building a sensor and an AI platform to train machine learning models to understand the behavioural cow data and detect if the cow is sick, in heat or calving. To be able to do this required building a more complete dataset on different behavioural patterns of dairy cows. The raw data set was built up using a sensor around the neck of the cow, based on an accelerometer, an electromechanical device used to measure acceleration forces. Based on the labelled data, a supervised model was trained to identify the behaviour patterns from the sensor data. By constantly training the models, it is possible to understand what the sensor data mean.

Figure 1 shows a graph of the behavioural pattern of a healthy cow. The vertical axe represents the amount of time a cow is showing a particular behaviour. We see a few meals, always at the same time of the day, when the farmers pushed feed in front of the cow, followed by bouts of rumination.

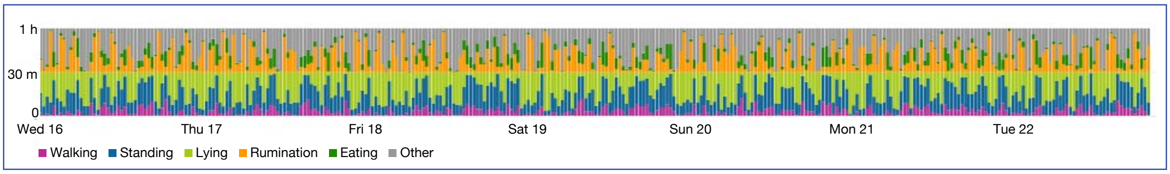


Figure 1. Behavioural pattern of a healthy cow

When the behavioural pattern of a healthy cow is known, anomalies in cow behaviour become apparent. In Figure 2, the cow seems to be ruminating well, but at a certain point stops ruminating completely. Anomalies like this can be indicative of different types of diseases. Some diseases are more acute (such as acute mastitis or digestive issues). Some diseases are developing over a longer period (e.g. lameness), and some are seasonal (e.g. heat stress).

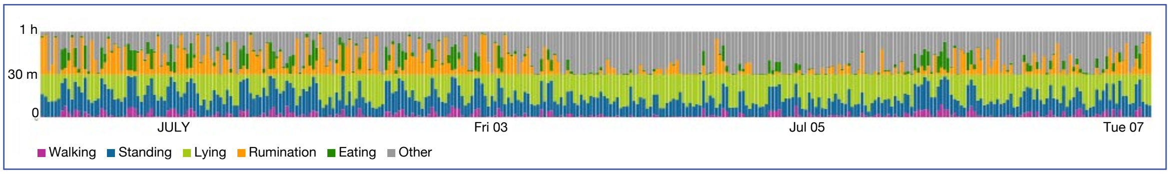


Figure 2. Behavioural pattern of a sick cow

Impact

Since the introduction of the Ida, the machine learning platform, many farmers around the world have begun using it and seen improvements in farm efficiency (20-30 percent), labour (reduction in hours per day), farm return on investment, insemination rates, pregnancy rates and disease prevalence and associated costs. For this case study, we delve deeper into the impact on animal health and antibiotic use.

Reduction in antibiotic use

The impact of the health models in Ida for dairy farmers is that sick animals can be detected two days before the symptoms are visible to the farmer. Connecterra began running a scientific field trial in January 2018 on two commercial dairy farms in Belgium and the Netherlands, each having a herd of 100 milking cows. The field trial was conducted within the context of the Horizon2020 Internet for Food and Farm project and supported by Wageningen University.

In the random trial half the cows received an Ida sensor. From the beginning of month 1, January 2018, the number of treatment days (all treatment with antibiotics) is less for cows with Ida, compared to those without the Ida sensors (Figure 3). The average for both farms for the whole period, January 2018 to December 2019, is 3.16 treatment days for non-Ida cows and less than 1 treatment day for an Ida cow. This means a reduction of -2.16 treatment days (-68 percent), resulting in less antibiotics. The difference between the Ida and non-Ida group was even bigger in 2019 compared to 2018. In 2019, the average number of treatment days for Ida cows was 0.71 days, compared to 3.16 days for the non-Ida groups, a difference of 2.45 treatment days (-77.5 percent). Fewer treatment days means less antibiotics per animal. Overuse and misuse of antibiotics in animals and humans is high on the agenda as it contributes to the rising threat of antibiotic resistance. Some types of bacteria that cause serious infections in humans have already developed resistance to most or all available treatments and there are very few promising options in the research pipeline. Using predictive intelligence in the form of AI can contribute to lowering antibiotic use in livestock and thus the formation of resistant bacteria.

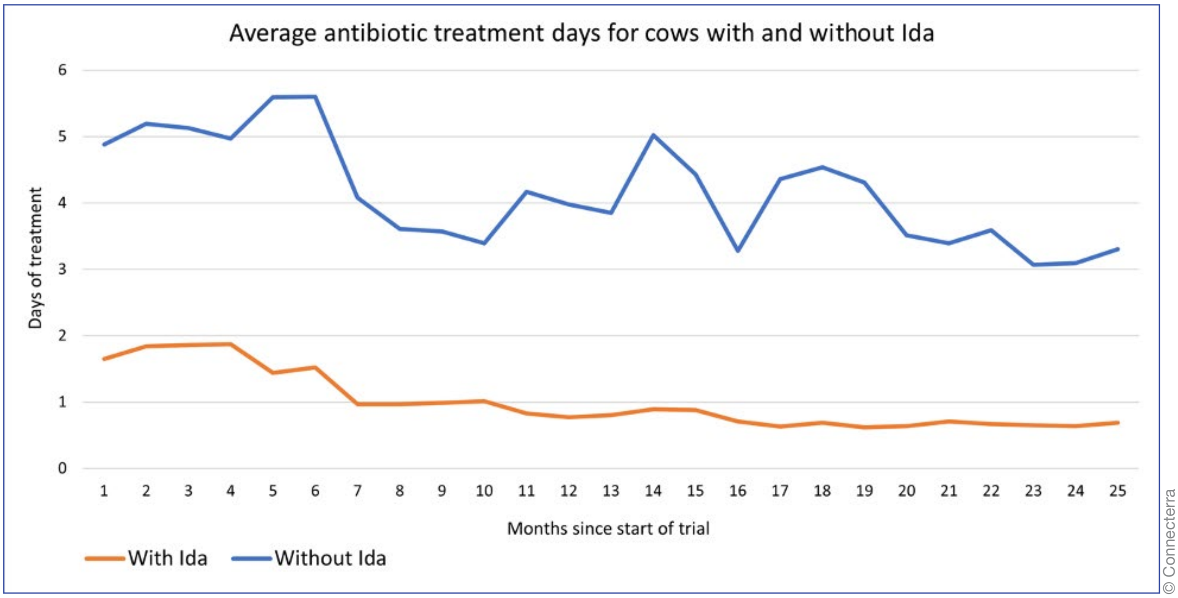


Figure 3. Average number of treatment days for cows with and without artificial intelligence sensors, average from two farms combined, January 2018-January 2020

Constraints and lessons learned

Predictive analysis and applying AI in livestock farming are not always that easy. Processing real world data from live animals and turning the data into useful insights is an interesting as well as rewarding challenge. Applying AI outside the lab and in the real physical world is pushing the technology to its current limits. Working with animals and farms around the world means a lot of unpredicted circumstances. One constraint in applying AI in agriculture is access to labelled datasets. The more data you have and the more labels you give the data, the better the results and the more sense you can make of the data, in this case animal behavioural data. Labelling is however time-consuming. Another constraint can be the data pipelines. How much data can you handle? If you connect millions of cows to a cloud platform, are you still able to handle and process the data? Considering that data are gathered from each cow, 24/7, the amount to be processed is huge.

The main lesson learned while developing an AI for the dairy industry is to start simply. If that works, then build more complex models, incrementally. It is also important to test the predictions of the models properly. Working with farmers also entails listening carefully to what they need from technology in their daily operations. Which are the pain points on a farm? What type of insights and advice does the farmer want? This is key when building a technology for farmers and encouraging them to use it. Also, the interface of the app, the easy to use dashboard and making data visibly attractive is a process that is just as important as the data themselves. When working with AI models, the interaction and feedback from farmers are crucial to constantly improve the platform.

Sustainability

The need to make farming more efficient and sustainable is key to feeding the growing world population. A sustainable dairy farm is one where cows are healthy and which takes care of animal welfare. Connecterra has shown that its AI driven platform can reduce the prevalence of diseases and cut antibiotic use by more than half. These results contribute to global goals of reducing overuse and inappropriate antibiotics, hence limiting the development and spread of resistant bacteria.

A sustainable farm is also one that is economic, financially viable, socially responsible and applies regenerative farming practices. AI can increase farm productivity and help farmers reduce production costs per kilogram of milk by making efficiency improvements on different levels (e.g. feeding practices, youngstock management, labour and breeding protocols).

Business sustainability

Production costs play a crucial role in the management of complex dairy farms. Keeping cows healthy can save a farmer a lot per year and reduce losses. This is especially relevant for costly diseases such as mastitis, lameness or pneumonia. Keeping cows healthy helps maintain a resilient farm. Healthy cows reduce veterinary costs or the losses incurred when a cow dies or has to be replaced. Ida's early illness detection can reduce days of treatment and hence total antibiotic use.

© Connecterra

Picture 2. Technology can make a big difference in improving basic farming practices in developing countries.

Developing countries

When we look at the social responsibility of the sector, we see great opportunities for dairy farming technology and AI in developing countries. Milk production in some is growing very rapidly and the key factor here is to produce more milk from the same number of cows by feeding them properly and looking after their health, while improving sustainability at the same time. Technology can make a big difference here as well as improve basic farming practices. Experiences in Kenya show that farmers who use the AI platform Ida can increase milk production and significantly improve basic knowledge on insemination time and heat detection. This empowers dairy farmers in rural areas to lift communities as a whole, to invest more in their farm and grow their business.

Stepping up efficiency of both local dairy farms in the developing world and dairy operations in the developed world are key to fill the food gap we will face in the coming decades. With the application of AI in dairy farming, Connecterra is contributing to solving five of the Sustainable Development Goals set by the UN: zero hunger, good health and well-being, industry innovation and infrastructure, climate action and life on the land.

AI and regenerative farming practices

Over the last decades, the dairy sector has already made great improvements in terms of milk production per cow and emissions per unit of product. When cows are healthier, they stay on the farm longer and produce more. This is because milk production increases per lactation. Improved longevity usually means higher profit per cow, as the cash flow of production pays off the investment made in raising replacement animals. The World Resources Institute showed that the more milk a cow produces, the less CO_2 output is created per kg of milk (Figure 4), reducing the environmental impact per kg of milk. The global dairy sector is also moving towards regenerative farming practices, embraced by some of the largest dairy processors in the world such as Danone. This is why Connecterra is part of Farming for Generations, a unique, global collaboration to support dairy farmers who adopt regenerative agricultural practices that preserve and renew our planet's resources, respect animal welfare and ensure the long-term economic viability of farms for the next generation.

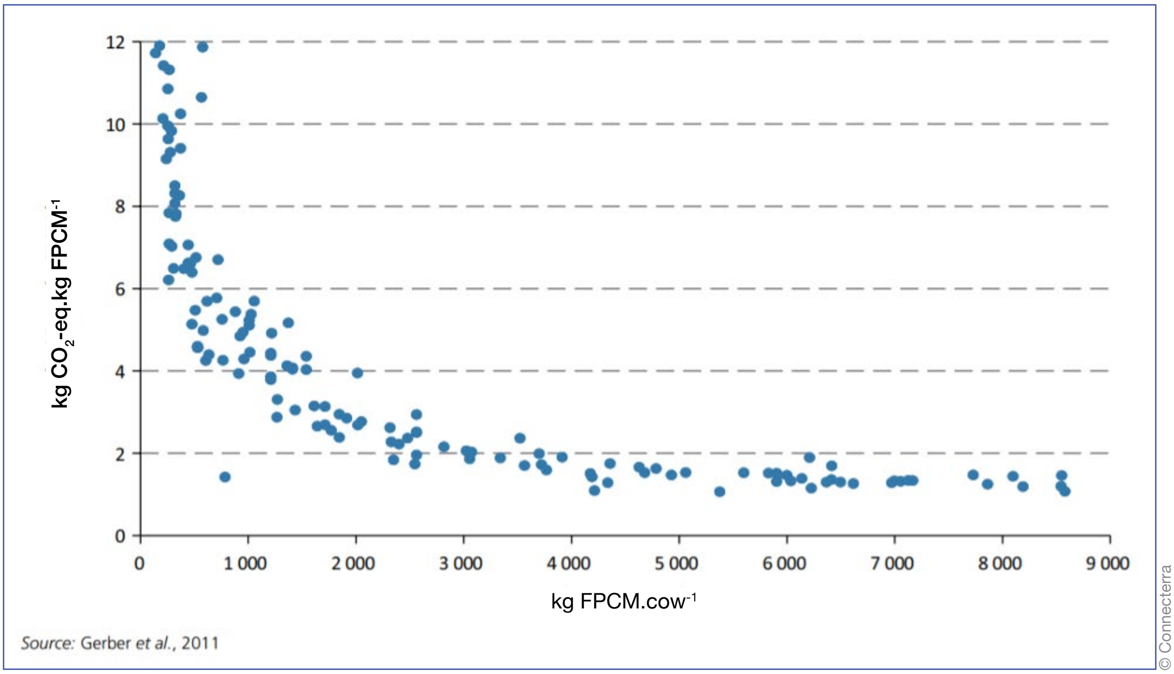


Figure 4. More efficient milk production decreases greenhouse gas emissions

Replicability

The data over two years in the scientific field trial in the Netherlands and Belgium show that Ida can be replicated and that cows with AI sensors are sick less often and need fewer antibiotics. The AI based technology continues to improve and iterate upon itself every time it encounters a new situation. This is the result of an ever-increasing volume of data, feedback from users (farmers) and the consistent and accurate labelling of data through experimentation and modelling. The company's hardware stack is designed from the start to support this use case, for instance, to be able to update the models in the sensors remotely. On top of that, integration with over a dozen farm management systems and third party data sources constantly improve the AI platform.

Augmenting farmer knowledge with AI

Peeyush Kumar, Andrew Nelson, Zerina Kapetanovic and Ranveer Chandra, Microsoft

FOCUS
App used for microclimate prediction, including temperature prediction and monitoring to optimise time of agricultural activities (including the application of chemicals), used in the United States of America

1. Introduction

It is the month of April and a farm in eastern Washington, United States of America, is producing wheat and lentil crops. Spring is just settling in while the low temperatures are slightly above freezing. Farmers are getting ready to spray their fields as the conditions become safe after a winter runoff and frost (Zheng *et al.*, 2015). The plants are significantly susceptible to certain herbicides at freezing temperatures, therefore, the farmer consults the local weather station for temperature forecasts, located in the closest metropolitan valley about 50 miles (80 km) from the farm. Three day predictions show consistent temperatures above freezing point. The farmer rents equipment and orders chemicals and starts spraying. A couple of nights the temperature in certain parts of the field drops below freezing and destroys around 30 percent of the crops. Despite forecasts from commercial weather stations, this is a common situation which can affect up to 50 percent of crops (Zheng *et al.*, 2015; Papagiannaki *et al.*, 2014; Moon *et al.*, 1993). This is because climatic parameters around the plant not only vary from the nearest weather stations but also between various regions of the farm.

AI (artificial intelligence) technologies are key to tackle the kind of problem presented above and many more as farmers face the challenge of feeding a growing population. Farms produce hundreds of thousands of data points on the ground daily. Farming technique which combines farming practices with the insights uncovered in these data points using AI technology is called *precision farming*. Precision farming technology augments and extends farmers' deep knowledge about their land, making production more sustainable and profitable.

This paper presents an example of an AI technology app used for predicting microclimate conditions on the farm. Microclimate is the accumulation of climatic parameters formed around an (approximately) homogeneous and relatively smaller region (Jones, 1993; Rosenberg *et al*, 1983). Knowledge of microclimate and microclimate predictions are of importance in agriculture (Singh *et al.*, 2018; Cai *et al.*, 2019) and forestry (Vanwalleghem and Meentemeyer, 2009).

This case study presents an outline and impact of a microclimate prediction framework: DeepMC. It predicts various microclimate parameters with 90+ percent accuracy at Internet of Things (IoT) sensor locations deployed in various regions across the world. The framework is based on a new deep learning approach which provides a comprehensive solution to the problem of predicting microclimates on farms. DeepMC predicts various climatic parameters such as soil moisture, humidity, wind speed, temperature based on the requirement over 12-120 hours with varying resolution of one hour-six hours. Multiple case studies and results from live deployments of DeepMC follow, reporting on average 90+ percent accuracy.

2. Context

Deploying AI solutions for predicting microclimate on farms is a challenging problem. First, data need to be collected from the farm before being processed through an AI service.

Second, these data need to be transferred from their location to the cloud where they are processed through the AI service forecasting microclimate. One of the biggest challenges deploying IoT systems for data-driven agriculture is connectivity. Since most farms are in rural areas, there is often little to no internet connectivity, this is crucial to enable seamless data collection. Consider the following scenario, where we want to collect data on a farm that spans thousands of hectares, metric is preferable. This would require deploying sensors across the entire farm field, which all need connectivity to convey information and in turn allow us to enable apps such as microclimate prediction or precision irrigation. Bringing this to fruition becomes even more challenging when considering the typical farming terrain. That is, signals must be able to travel through a dense crop canopy at long distance, often with no line of sight.

Third, the methodology used to build AI models which forecast microclimates needs to be accurate, reliable for daily use, replicable across farms and adaptable to various uses. Climatic parameters are stochastic (a random process) in nature and quite challenging to model for prediction tasks on farms.

1. High prediction accuracy: Generating high accuracy results is an obvious challenge for any real world deployment of a machine learning solution. In the context of microclimate predictions, a small quantity of labelled datasets, heterogeneity of features and the non-stationary nature of input features all make the learning problem to generate highly accurate results quite challenging.
2. Reliability for frequent use: Non-stationarity of the climatic time series data makes it difficult to reliably characterize the input-output relationships. Each input feature affects the output variable at different times, for example the effect of precipitation on soil moisture is instantaneous while the effect of temperature on soil moisture accumulates over time.
3. Replicable for farms across the world: Any system for microclimate predictions is expected to perform across various terrains, geographic and climate conditions. In practice, good quality labelled data are generally not available and even if accessible may not be available for all terrain, geographic or climatic conditions. Therefore, smarter techniques are required to transfer a model learned in one domain to another with little paired and labelled datasets.
4. Adaptable for multiple use cases: It is also a difficult space to adapt results for multiple use cases. Various factors influence the trend of a particular climatic parameter of interest. For example, soil moisture predictions are correlated with climatic parameters such as ambient temperature, humidity, precipitation and soil temperature (Hummel *et al.,* 2001), while ambient humidity is correlated with parameters such as ambient temperature, wind speed and precipitation (Zou *et al.*, 2017). This creates a challenge for a machine learning system to accept vectors of varying dimensions as input to replicate predictions for different use cases.

The output information needs to be presented in a way that helps the end user (the producer/farmer in most cases) in their decision-making.

3. Methodology

DeepMC addresses the problems outlined above. It uses FarmBeats (Vasisht *et. ai.*, 2017) platform and TV White Spaces (TVWS) technology[5] to address problems of data collection, data transmission and data presentation. In addition DeepMC also utilizes the nearest available weather station forecasts to determine the relationship between various climatic parameters.

FarmBeats: DeepMC uses FarmBeats (Vasisht *et. ai.*, 2017) platform to collect climatic and soil data from multiple sensors around the world. FarmBeats is an end-to-end IoT platform for data-driven agriculture, which provides consistent data collection from various sensor types with varying bandwidth constraints. We chose the FarmBeats system for this work because of its high system reliability and availability, especially during events such as power and internet outages caused by bad weather – scenarios that are fairly common for a farm. The data collected by FarmBeats IoT sensors are placed in the cloud and accessed there. We also use the FarmBeats platform dashboard to deliver microclimate predictions to the end-users of their Azure marketplace offering.[6]

TVWS technology: The challenge of transmitting data from farm locations to a computer unit is solved by using a new technology, TVWS. These are an unused TV spectrum that can extend internet connectivity to locations that may be a great distance apart. This technology is ideal in agricultural scenarios for two reasons. First, since farms are in rural areas there is a lot of unused TV spectrum available that provides large amounts of bandwidth for data transmissions (a single TV channel in the United States of America has a 6MHz bandwidth). Second, TV spectrum spans the lower megahertz UHF and VHF bands, ideal for long-range communication even through dense canopy.

Weather station forecasts: These are collected for training and inference through commercial weather stations. Models in DeepMC are trained and tested with various weather data providers – DarkSky,[7] NOAA,[8] AgWeatherNet,[9] National Weather Service[10] and DTN.[11]

5 https://rdlcom.com/tv-white-space/
6 https://azuremarketplace.microsoft.com/en-us/marketplace/apps/microsoftfarmbeats.microsoft_farmbeats
7 Official website: https://darksky.net/dev
8 Official website: https://www.ncdc.noaa.gov/cdo-web/webservices/v2
9 Official website: https://weather.wsu.edu/
10 Official website: https://www.weather.gov/documentation/services-web-api
11 Official website: https://cs-docs.dtn.com/apis/weather-api/

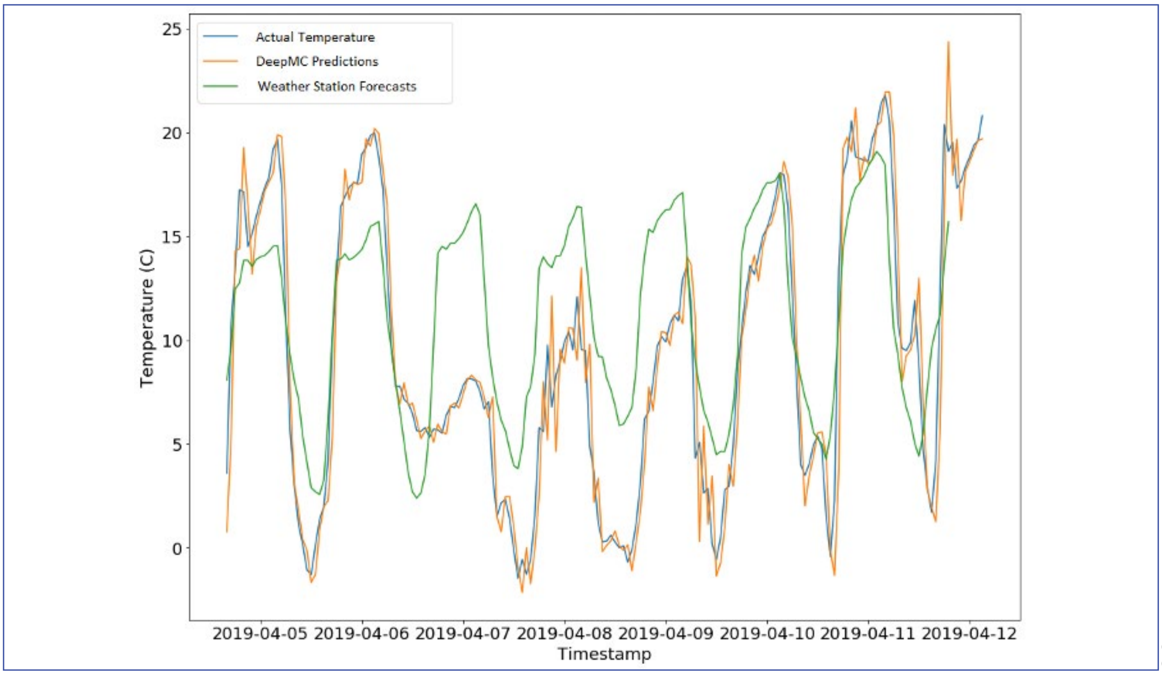


Figure 5. DeepMC microclimate temperature six day sequential predictions with a resolution of six hours

3.1 DeepMC - a deep learning based framework for microclimate predictions

The prediction problem is solved by using a deep learning approach to combine weather station forecasts and IoT sensor data in a special way. Each of the challenges identified in the third point of the two are addressed.

1) Result accuracy: Instead of predicting the climatic parameter directly, we predict the error between the nearest commercial weather station forecast and local microclimate forecast. This is based on the hypothesis that hyper-localization of weather station forecasts is easier to learn than the relationships of the predicted climatic parameter with the predictor climatic parameters from ground up. DeepMC achieves acceptable accuracy using this design model with reported 90+ percent MAPE (mean absolute percentage error) accuracy across various regions in the world.

2) Reliability: In order to reliably capture varying effects of climatic data a solution needs to capture multiple trends in the data in a stationary way. DeepMC utilizes a multiscale decomposition approach to capture these effects. This approach decomposes the input signals into various scales capturing trends and details in the data and allows them to be modelled in a repeatable, reliable way.

3) Replicablity: DeepMC utilizes a specialized deep learning model, called GAN (Goodfellow *et al.*, 2014), to transfer learning from source farms to target farms around the world.

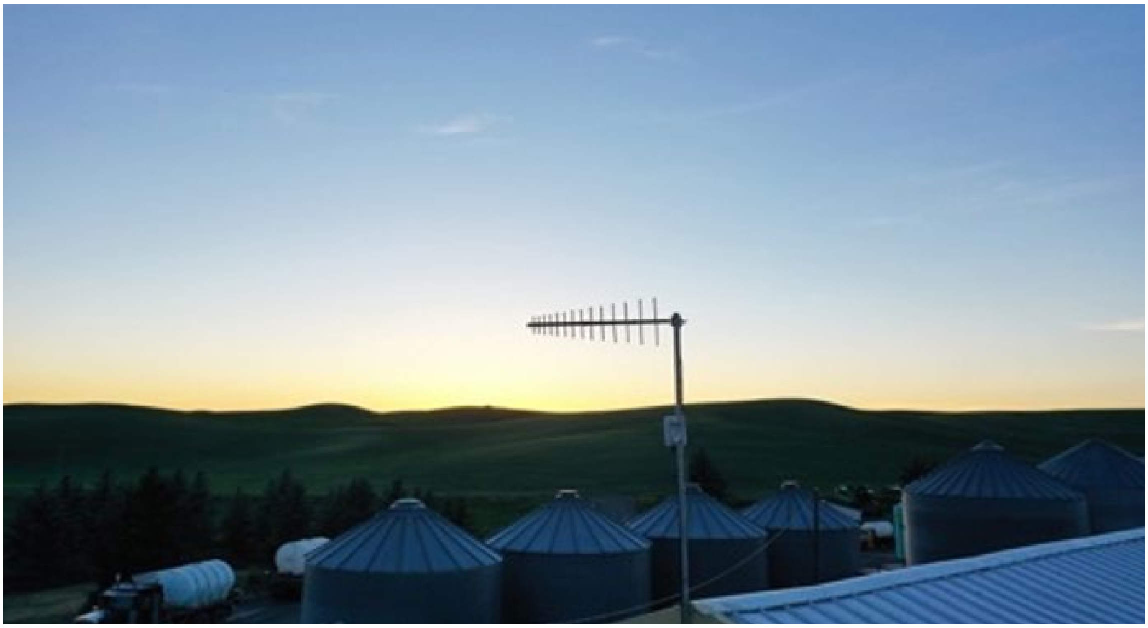
4) Adaptability: All of the techniques combined together in a specialized architecture enable adaptability across multiple use cases on the farm.

4. Impact

DeepMC is used across many different regions of the world where FarmBeats (Vasisht *et al.*, 2017) technology is deployed. In this section, we present three agricultural applications which are a projection of common situations affected by weather conditions. We also show some results in comparison to common models used to solve prediction tasks.

4.1 Scenario 1 - Spraying herbicide: microtemperature predictions

This scenario is the one presented in the Introduction. Nelson Farm is located in the eastern portion of Washington State in a region called the Palouse. It is an area known for its rolling hills and crops such as wheat, lentils, peas, garbanzo beans and canola. The area is at the foothills of mountain ranges and the combination of the rolling hills and mountains make weather forecasts less accurate. Many farmers own and rent land.



Picture 3. A TV White Spaces deployment on Nelson farm

Some of those rents are a crop share so the landlord and the farmer working the land are both affected by decisions made. There are also many research test plots scattered throughout the area that benefit from the farmer's advice on when to complete certain field operations. The farmer operates on approximately 9 000 acres of land across a region which is quite hilly and there are many distinct microclimate regions on this farm. Climatic parameters vary significantly among various regions of the farm and also between the nearest commercial weather forecast provider and the readings on the ground. The farmer uses DeepMC predictions for temperature forecasts at specific locations on the farm.

We deployed TVWS and FarmBeats sensors at Nelson Farm. The farmer has internet connectivity at his home, but it cannot cover the vast size of his farm that spans approximately 9 000 acres (3 600 hectares) across 45 miles (72 km). To remedy this, the TVWS base station connects to the internet at the farmer's home and extends coverage to TVWS clients out in the field (see

Picture 4). The TVWS links between the base station and clients are up to 13 miles (21 km) in this deployment and we used several FarmBeats sensor boxes to collect data (see Picture 4). The sensors record wind speed and direction, ambient temperature and soil moisture and temperature.

The FarmBeats system has been on Nelson farm for 24 months and has provided numerous insights that helped improve overall productivity. For instance, the farmer consults DeepMC for temperature predictions at specific locations to plan logistics and operations when spraying herbicide. These experiments were conducted in the spring of 2019 and 2020, using daily microclimate predictions when spraying wheat, lentils, peas and garbanzo beans, to plan the days when fields could be sprayed with certain herbicides, sometimes to avoid freezing weather and others to avoid overly hot weather.

Figure 6 shows a six day forecast with a temporal resolution of six hours, comparing results obtained by DeepMC with Dark Sky weather forecast (from the nearest station) and the actual temperatures recorded using IoT sensors in retrospect. Based on DeepMC's predictions the farmer postponed his spraying from 7 April 2019 to 11 April 2019 as DeepMC predicted below zero temperatures. If the farmer had relied on weather station forecasts consistently showing temperatures above freezing (>5° C), then he would have risked losing up to 30 percent of his crop. The farmer was also able to reallocate his labour to other tasks during the days when spraying herbicide. In the fall season the farmer can give more notice to his employees about when they are needed at the farm since operations cannot be done in freezing conditions. This advance notice gives them more time to rest whereas they used to have to wait for an early morning call before planning their day. In many places, especially smallholder farms, this is significant enough to determine whether or not farmers can achieve basic sustenance of food and supplies in the coming year.

Picture 4. A FarmBeats sensor deployed on Nelson farm

4.2 Scenario 2 - Phenotyping research: micro soil-moisture predictions

The producer here is interested in experimenting with different growing techniques for vine tomatoes which are susceptible to rot if grown too close to soil with high moisture values. Generally, growers use trellises to lift the vines and provide structural stability, adding further challenges to managing the crops over the growing season. This producer would like to grow tomatoes without trellises but this depends on being able to predict local soil moisture values accurately. Using DeepMC for advice on micro soil-moisture conditions, Figure 7 shows the results with a recorded RMSE value of 3.11 and MAPE value of 14.03 percent (implying 85.97 percent accuracy). The predictors for micro soil-moisture are: a) from the IoT sensors – ambient temperature, ambient humidity, precipitation, wind speed, soil moisture and soil temperature; b) from the weather station – historical soil moisture forecasts.

4.3 Scenario 3 - Greenhouse control: microhumidity predictions

In this scenario, the producer stores garbanzo beans in a grain tank. To control climate conditions inside the tank, fans pull in air from outside to regulate temperatures inside the greenhouse. The speed and duration of the fan control depends on the immediate humidity levels in the outside air. The producer consults DeepMC for advice on control of the grain tank fan. The results are shown in Figure 7. The predictions are plotted for the 12th hour over one week with a resolution of one hour. The RMSE recorded is 5.54 and MAPE is 5.09 percent (therefore, the MAPE accuracy recorded is 100 percent – 5.09 percent = 94.91 percent). The model was trained on a stock dataset from a different farm where sufficient paired data were available and transferred at this location. The predictors of microhumidity are: a) from the IoT sensors – ambient temperature, ambient humidity, precipitation, wind speed; b) from the weather station – historical ambient humidity forecasts.

5. Innovation and success factors

This work develops a comprehensive microclimate prediction framework for use with multiple input-output paired climatic parameters. We highlight three real world deployments which characterize a diverse set of conditions. We conduct a comprehensive validation of DeepMC across various regions around the world and various microclimatic parameters. The predictions are used through real world deployments of the FarmBeats system in Ireland, Africa and various states in the United States of America. The results are computed for predictions of local temperature, local wind speed, soil moisture, soil temperature and humidity. The framework is generalizable to other input-output combinations of the climatic parameters.

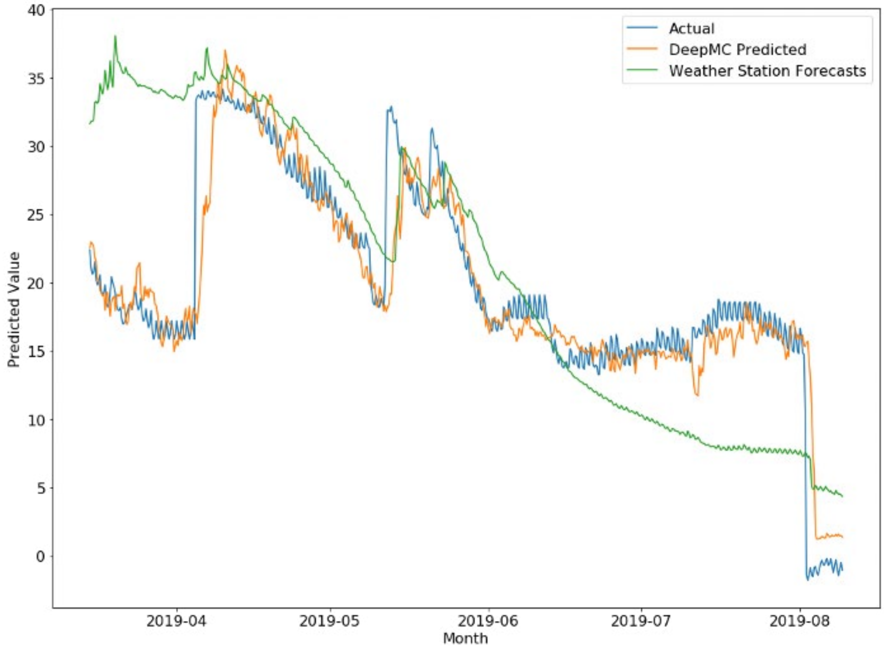


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Figure 6. DeepMC microclimate soil moisture fourth day prediction with six hour resolution over a period of ten months

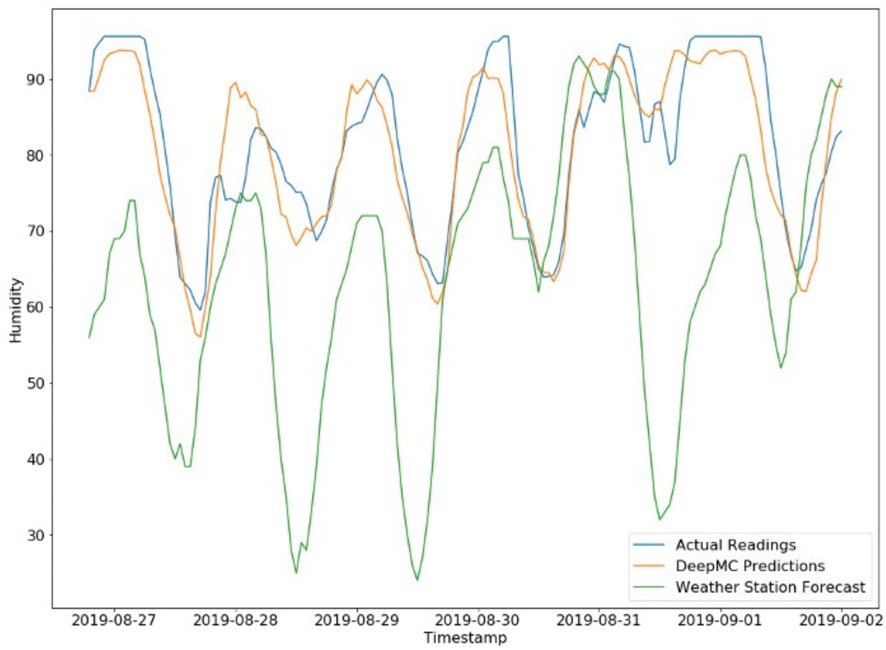

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Figure 7. DeepMC Microclimate humidity prediction at the twelfth hour with a resolution of one hour over one week

This framework is an example of how AI technologies can augment farmers' knowledge to help them make better decisions on the farm. We address some of the most difficult problems in precision agriculture viz-à-vis data collection on farms which are remote and computation to surface insights from those data. The factors which contributed to the success of this work were the innovation that went into the research along with collaboration from farmers facing the problems we set out to solve. This close link between development and application site fuelled the success of this project.

6. Sustainability

Environmental sustainability: AI-based solutions allow for better cost control through better predictions based on relatively affordable weather stations. Their data allow farmers to apply chemicals with better timing making them as effective as possible. Many weeds controlled by chemicals are gaining resistance, so the more effective the chemical at the time of application, the more unlikely the weed will develop resistance to it with less use of chemicals overall. The other way it helps environmentally is that farmers can better monitor crops growing far apart from each other and not apply the same practice in each field, instead managing each field according to its microclimate for that year.

Operational sustainability: We follow a partnership driven model to promote uptake of the solution described in this article. We work closely with some of the major organizations in agriculture[12] (corporations, governments, cooperatives, consortiums, non-governmental organizations, etc.) who have a wider reach into the farmer ecosystem. The AI solutions are deployed in partnership with these organizations, where we share AI generated insights on market advisories, and inputs/outputs to farm operations. This creates a synergistic environment and the right incentives for organizations to deploy these solutions on the farm. The organizations benefit from the advice (such as predicted seed intake, estimated crop yield etc.) and farmers benefit from input insights (such as microclimate predictions, irrigation advice etc.). This partnership driven model has been found to scale adoptions to a wide demography of farms around the globe.

The cost factor is another key requirement to make AI solutions more practical and sustainable. The key innovations in the technology presented here lower the cost of deploying sensors and digital operations on the farm. The FarmBeats platform makes it cheaper to deploy and integrate sensors directly in a central datahub by its key innovations in networking technology, storage and compute on the edge framework. This central data aggregation and deployment platform also enables running AI solutions for a fraction of the cost and the PaaS (platform as a service) model allows for scale which drives down costs per user.

As presented in this case study, a key challenge for an AI/digital framework to be actionable on the farm is the gap between how producers think and conduct their operations, and the complexity of using technology and digital literacy. As part of deploying the solution we also developed solutions to help educate the next generation of farmers on how they can use technology to make advances in agriculture. We developed student kits, a plug-and-play platform to teach students how data can be used to provide meaningful and actionable insights for farming applications. The student kit comes with several sensors (e.g. soil moisture, soil temperature, light intensity) and a Raspberry Pi running Windows IoT Core that is ready to

[12] For example: https://www.businessinsider.com/microsoft-and-land-olakes-new-partnership-tackles-the-digital-divide-2020-7

interface with an IoT dashboard. The IoT dashboard displays all incoming sensor data that the students can interact with, learn how to interpret data and use the data to make intelligent decision for their farms.

We partnered with the Future Farmers of America (FFA)[13] to distribute FarmBeats student kits to FFA chapters across the United States of America. Moreover, we work with FFA to provide workshops and hackathons for teachers to learn how to educate students about agrotechnology and develop lesson plans around the student kits, ultimately expanding each student's view of how farming practices can become more cost effective, productive, and sustainable by leveraging AI and IoT technology.

7. Constraints

There were a few challenges encountered during the development and deployment of the DeepMC framework. The development challenges are described in Section 2 and how the solution presented here addresses them. Operationally, the challenges in Section 6 on sustainability highlight the constraints to adapting this technology on farms and steps taken to overcome them.

8. Replicability

This framework is replicable for use in other contexts. The results presented in Section 4 show how DeepMC can be adapted for various farms across multiple conditions. As it stands this framework is easily scalable in a cloud environment.

DeepMC can also be used in other contexts which need microclimate predictions, such as forestry, maritime environment, etc. Using it in non-farm conditions will need model retraining from scratch but without any change in the underlying architecture.

9. Testimony

Andrew Nelson, Nelson Farm
"Utilizing AI allows farmers to have another tool at their disposal. The ability to quickly apply the results that AI models produce is a great advantage. The other large benefit is that AI can allow for other technologies to have more realized benefits. TVWS sensors that are placed throughout the farm can allow multiple predictive models for different terrain and microclimates. AI has brought a new perspective on existing data, it can combine aerial imagery and ground soil moisture sensors to give insight on soil moisture that is not easy to see while walking through the farm, even if the farmer were to take a soil moisture reading at multiple locations. Farmers are then able to utilize more data to make their decisions that would otherwise be difficult or too time consuming to analyze on their own.

During busy seasons, farmers are already working during all available daylight, any time savings allow the farmer more time to tend to their crops which usually allows for higher yield potential. The future predictions that AI provides give farmers more insight on how to maximize their investment of time and money into the current crop. It has allowed for larger scale testing of different farming techniques that have improved farming practices in terms of profitability, sustainability, and sometimes both."

[13] Official website: https://www.ffa.org/

XAG smart agriculture system: reshaping the future of an AI-powered smart farm

Olivia Zhou, XAG

FOCUS
Integrated management of agricultural production: AI plays the role of data analyst to assist farmers in making scientific decisions on time, location, and resource utilisation of each farming activity; used in China.

1. China's agriculture: emerging trends and challenges

China's small-scale farming has been impressively feeding one-fifth of the world's population with less than 10 percent of its arable farmland, even though its smallholder economy was once regarded as the greatest restriction on its agricultural and rural development. For thousands of years, Chinese agriculture has predominately consisted of family-operated smallholdings with small, scattered, irregular plots of land. The use of large ground-based machinery is largely constrained by China's smaller land size and varied terrains (e.g. hills, mountains, terraces and plateaux). According to the Ministry of Agriculture and Rural Affairs the number of smallholders in 2019 accounted for 98 percent of China's agricultural production operators. Around 230 million people, with an average holding of less than 1 hectare, engage in agriculture to provide for the country's 1.4 billion population. This means that one single farmer can only produce enough food for five people, while this ratio can reach 1:100 in developed countries. In the meantime, vigorous new types of agricultural business such as family-run farms, farmers' cooperatives and corporate-owned farms have emerged as the result of accelerating land circulation, indicating the future trend of scale operation as well as increasing demand for smart farming tools.

However, no matter the size of the farms, China's current agricultural production system still operates in a traditional labour-intensive, resource-consuming manner. These farms rely heavily on manual labour for integrated crop management, such as land scouting, fertilisation and crop protection, which take up 70 percent of time throughout the whole farming process. Yet the mechanisation level of most of these activities stagnates at only 7.5 percent, substantially lower than for tillage, sowing and harvesting. During the planting season, for example, groups of farmers and hired agronomists have to conduct regular field scouting to check for pest infestation, crop growth performance and soil health condition. They have to painstakingly spend hours every day on the sampling fields to collect information using pen and paper or a handheld geotagging device. On larger farms it is impossible for a manual workforce to cover all land plots, which means missing some crop abnormities and thereby lower crop yield. With long hours toiling in the fields, many farmers unfortunately develop a series of chronic health problems such as back injury, skin disorder, respiratory illness, etc.

Overuse of pesticides, fertilisers and agricultural water are another sustainability issue that plagues China's agriculture sector. It is estimated that 70 percent of potable water is used for agriculture, but 60 percent of potable water is contaminated by industrial and agriculture chemical pollutants. Without scientific guidance on when, where and how much to spray, carrying a backpack sprayer of agrochemicals to sweep across the entire field remains the norm in many farms, especially those on rugged, sloped terrains inaccessible for medium-to-large ground equipment. Field workers with no protective measures are fully exposed to pesticide spraying over long hours.

Labour dependence has also increased the vulnerability of China's agricultural system to the emerging crisis of rural labour shortfall and an aging farming population. During the past two decades, due to accelerated urbanisation, the percentage of rural population has decreased from 64 percent to 40 percent in 2018. As young people flock to the cities for better employment opportunities, elderly farmers over 50 are now the major rural workforce in agricultural production. If action is not taken promptly, the future of food supply may be threatened when the older generation of farmers retire with no successor to tend their farms. This is where artificial intelligence (AI) can deliver the key enabling factor for smart agriculture, a new form of agricultural production ecosystem based on digital technologies and precision farming devices.

2. Constraints to AI application in agriculture

A variety of industries, such as healthcare, automobiles, manufacturing and finance have consistently witnessed important milestones in AI applications. However, due to the lower level of modernisation and fewer information sources, Chinese agriculture is lagging behind with most of its AI explorations, lingering in the laboratory stage. Unlike highly digitalised urban areas, the remote rural community is faced with lack of digital farming infrastructure or intelligent production tools. While city dwellers can grasp a full picture of the traffic and pinpoint each location on their app, farmers do not have any navigation network to guide their agricultural operations. And the bits of sampling data recorded manually from crop scouting cannot be coded into algorithm development. Without adopting digital farming devices, it is impossible to collect enriched farm data to feed the AI engine for deep learning. The realisation of an AI-powered farm must be premised on the basis of agriculture big data, obviously absent in the existing labour-dependent system.

3. Methodology: XAG's AI-powered smart agriculture solutions

XAG believes that agriculture AI is born from land rather than the algorithm designed on a computer. With years of practical experience in autonomous field application, XAG has developed a smart agriculture solution that integrates the use of unmanned aerial system (UAS) robots, automated steering system and management software as catalysts to unleash the huge potential of AI technology. These six product lines consist of XAG agricultural UAS, XAG R150 unmanned ground vehicle, XAG XMission survey UAS, XAG autopilot console


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Figure 8. XAG smart agriculture solution

(APC), XAG agriculture IoT system (XIoT™), and XAG smart agriculture system (SAS). It starts with leveraging the survey UAS and IoT system to capture digital field maps, crop images and environmental data in the prescribed areas, followed by the analysis of XAG artificial intelligence (XAI) to gain an overall insight into farmland conditions. Based on AI-backed decisions, XAG's unmanned devices can conduct safe, precise operations of seeding, fertilising, and crop spraying at the appropriate time to grow more with less.

The three major processes of farm management–perception, decision-making and execution – are seamlessly linked together on the XAG SAS, where AI plays the role of data analyst to assist farmers in making scientific decisions on time, location, and resource utilisation for each farming activity. Commercially launched in late 2019, the SAS system is designed as a highly visualised software platform for technology-driven farm management. It creates a close-looped ecosystem in which autonomous devices and AI applications are integrated to enable crop indicator based smart in-season agronomic planning and execution.

3.1 Perception: building digital farming infrastructure to enable AI applications

To remedy the lack of digital farming infrastructure, XAG has set up over 2 300 RTK (real time kinematic) base stations that facilitate the adoption of the BeiDou navigation satellite system in China's 35 000 rural villages. XAG's survey UAS photograph high definition digital field maps which cover the entire farmland. This is building up a centimetre-level agricultural navigation network that enables standardised LBS (location-based service) of drones, robots and autopilot systems in farming areas.

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Picture 5. Building digital farming infrastructure

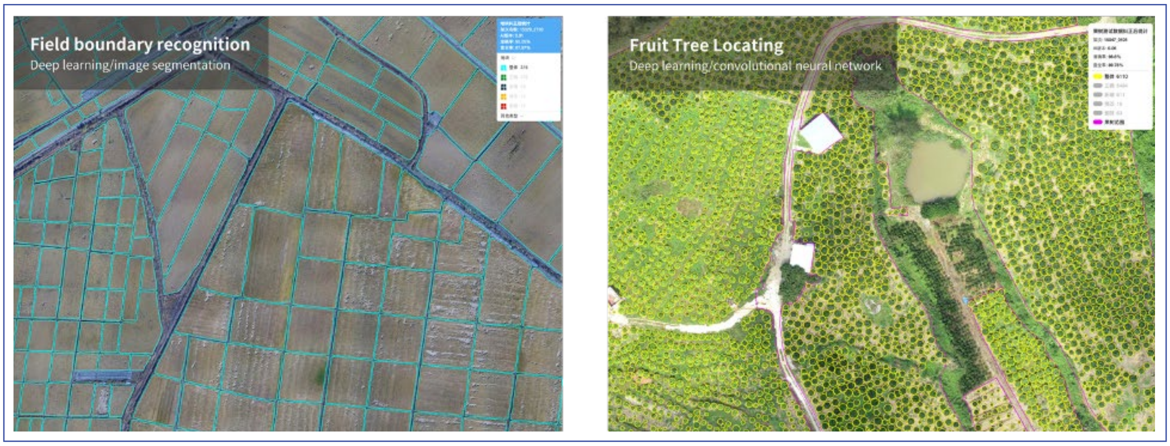
While drones fly in the sky to capture an overall farm image, the solar powered XIoT™ system continuously takes high resolution pictures of a specific crop variety and collects ground soil/weather data. These digital field maps and farm data are automatically transmitted to and neatly displayed in the SAS system, with each land plot as uniquely numbered metadata. Farm owners do not need to put workers into the fields to scout the crops or geotag their locations. Through checking digital maps with a few taps on the app interface, they can have an overview of their entire farmland or detailed information on certain land parcels. The availability of big data in agriculture lays a solid foundation on designing AI algorithms for reliable field applications.

3.2 Decision-making: XAI provides data analytics and timely diagnosis

XAG artificial intelligence (XAI) is an AI cloud computing platform developed to achieve field insight and crop growth objectives. With a large amount of agricultural production data every day, the SAS system provides a series of XAI-powered apps to assist farm owners in measuring the growth of various crops in different land plots, identifying abnormal conditions such as pests and weeds and evaluating the efficacy of fertilisation and crop protection management.

• *High accuracy field mapping*

Before deploying autonomous equipment to conduct precision farming operations, the drone pilots operate the XMission survey UAS to map the designated fields covering 40 hectares per hour. XAI automatically recognises all the boundaries and obstacles within the high definition field maps as well as calculating the land area of each parcel. For orchard management, the position of each fruit tree, including its centre and perimeter, can be accurately pinpointed with a recall ratio and precision ratio as high as 98.60 percent and 98.04 percent respectively. One second can identify nearly 7 hectares of fruit trees. This application is based on deep learning techniques, namely image segmentation and convolutional neural network (CNN). It allows drones and robots to precisely target prescribed areas or a single tree for crop spraying while avoiding obstacles such as utility poles and overhead cables, to ensure operational safety. In the past, people had to walk within and around each land parcel to geotag the field boundaries and on-farm objects, a laborious working process especially on rugged, irregular or waterlogged fields.



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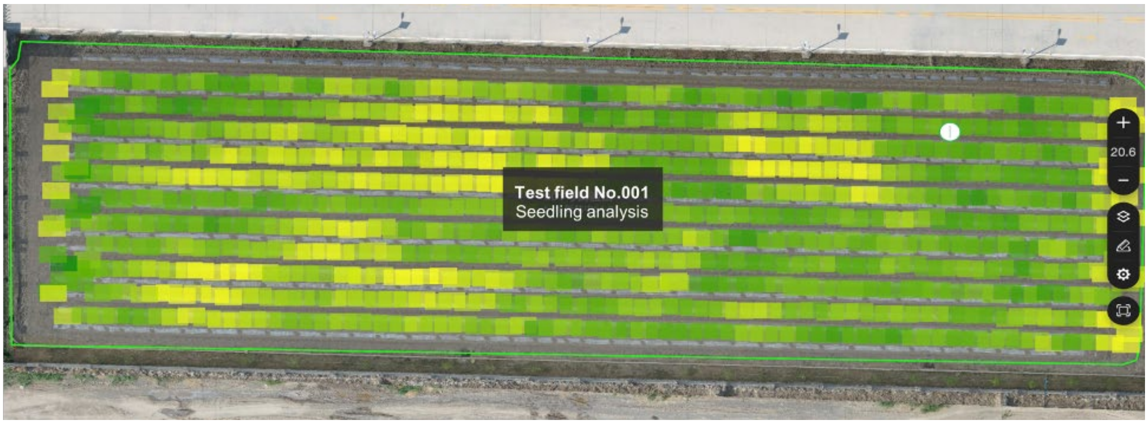
Picture 6. XAG artificial intelligence identifies field boundaries and fruit tree location for field mapping

• *Optimising seedling population*

During the seedling stage of crop growth, the number of healthy individual plants per unit ground area is considered a simple, yet essential factor that links to plant density and influences final crop yield. An optimum seedling population must be obtained to achieve desirable crop production. On the digital field maps, XAI is successfully programmed to identify the shape of each individual plant and calculate the seedling population of each land plot. It directly reveals whether the seedling population falls within the optimum level, so that land managers can make timely decisions on appropriate cultivation measures. When the SAS system indicates that the number of crop seedlings has fallen below the target value, gap filling via transplanting should be promptly implemented in specific areas before the thinning period.



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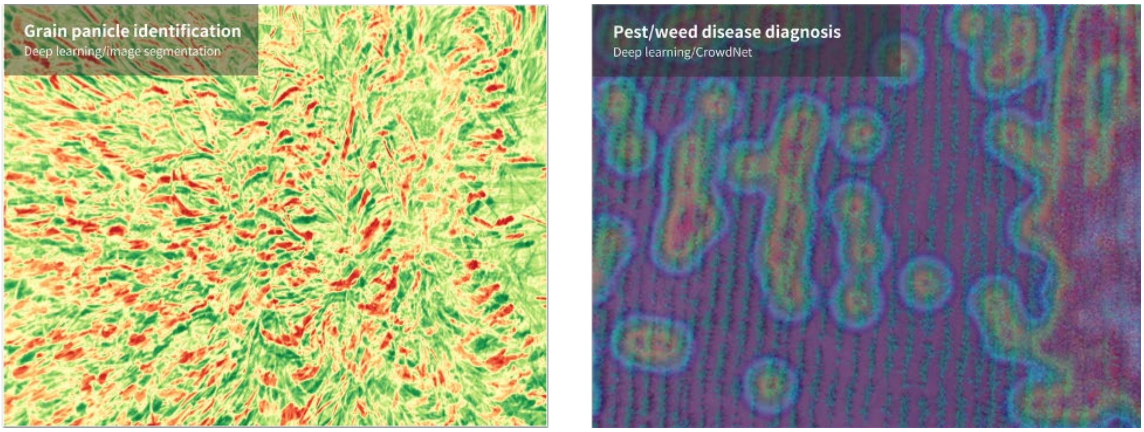
Picture 7. Each plant seedling is accurately identified in the SAG artificial intelligence system

• *Crop growth modelling*

Cotton is one of the important high value specialty crops in China, where production in 2019 constitutes 23 percent of the world's total. In north-west China, the country's major cotton producing region, the cotton growing season is relatively short due to lower temperatures in spring and autumn. The short-dense-early cultivation technique – reduced crop height, high plant density and early maturity – has been widely adopted to improve unit yield. The height of cotton plants needs to be carefully monitored and controlled in optimal range to avoid excess growth. This was traditionally done by setting up fixed points within the cotton field to measure the height manually with a ruler. Instead, XMission survey UAS and XAI are combined as an innovative solution to create 3D models for plant height distribution on the cotton field maps. The SAS system records the height of each individual plant and overall distribution levels to indicate which part of the cotton plant is growing too fast. Land managers and farmers can easily plan how to adjust the speed of crop growth through chemical regulation, fertiliser application or irrigation. An optimum plant height helps the cotton grow into the ideal shape and structure, resulting in a higher number of bolls and increased yield.

• *Anomaly detection of crop diseases*

When installing with the multi spectrum camera, the XMission survey UAS also takes remote-sensing farm images that capture spectral variations to reflect the state of crop health. Abnormal changes, such as the presence of harmful pests, invasive weeds, or other crop diseases, can be accurately identified on the digital field maps through the use of the normalised difference vegetation index (NDVI). Sparse vegetation coverage can also be recognised to provide locations and treatment areas for rehabilitation of degraded land. Based on these NDVI results, XAI generates AI prescription maps to instruct farm owners on the proper use of seeds, fertilisers, or pesticides.



Picture 8. XAG artificial intelligence analyses remote-sensing maps to identify grain panicle and detect diseases, presented in different colours

• *Yield estimation*

Other AI applications of the SAS system include estimating grain yields of rice, wheat and maize through panicle counts during the ripening stage. The panicle number is an agronomic determinant of final crop yield. It is traditionally obtained by sending field workers to manually count panicles of the sampling plants one by one on selected land plots, an inefficient, laborious method which falls short of accuracy. To resolve this, deep learning models are developed to train XAI to identify the locations of individual panicles and then calculate their total number with remote-sensing images. Having a more precise estimate of crop yield, farm owners can make practical plans for future market transactions to improve their profitability.

3.3 Execution: AI prescription map to guide precision farming operations

Through extrapolating the value behind field images with the application of XAI, the XAG SAS system helps farmers alleviate their physical burden and make smart decisions on best farm practices. These smart decisions are accurately executed by XAG agricultural drones and robots developed to replace manual labour and traditional large ground equipment.

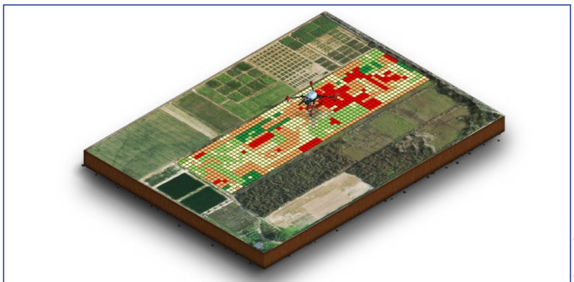


Figure 9. Artificial intelligence prescription map enables variable-rate application

XAG agricultural UAS integrates two major functions – crop spraying and granular spreading – into one single drone platform. With the guidance of AI prescription maps, drone swarms can navigate themselves on their pre-programmed flight route with centimetre-level accuracy, while releasing the correct amounts of seeds, fertilisers, or pesticides precisely onto the target areas without overlaps or misses. Since the drone can adjust droplet size, the flow rate and spray width during flight, seeding, fertilising and crop spraying can now be conducted only where they are needed, such as places with sparse vegetation cover or crops infected with pests, diseases or invaded by harmful weeds. For cotton planting, the growth regulator is only applied accurately to the areas growing too fast as indicated by the 3D height distribution map. Compared to indiscriminate spraying, variable rate application (VRA) helps reduce the use of pesticides by 60 percent as well as conserving agricultural water by up to 90 percent.

The XAG R150 unmanned ground vehicle (UGV) also participates in automated farming operations across demo farms in China. It can operate with a 360° pan lilt unit jetsprayer which supports any AI solution on various terrains. Fruit growers are using the R150 in orchards where the robot can flexibly traverse narrow spaces to spray the entire fruit tree giving powerful penetration.

© XAG

Picture 9. XAG Agriculture utility vehicle and agricultural unmanned areal system conduct AI-backed precision spraying or seeding

4. Digital transformation of a cotton farm in north-west China

4.1 AI applications in cotton management

In China, cotton growing has become one of the largest markets for agricultural drones and IoT system, being widely adopted to spray crops and monitor field conditions. Owing to the abundant light, rich heat resources and lower precipitation, north-west China has the ideal climate to grow high quality cotton, accounting for 76 percent of the country's planting area and 84.9 percent of total production last year. With greater use of unmanned digital devices in this region, AI has gradually made its way into the cotton farming industry.

Since 2019 XAG has been collaborating with Lihua Cotton Industry Co. Ltd in north-west China to explore the construction of an AI-powered smart farm. The whole set of XAG's smart agriculture solutions has been introduced to Lihua's demo farm, 1 000 hectares of cotton field. Currently, one of its major AI applications is examining seedlings, which previously required labour to count. For every land parcel, technicians randomly selected three sampling points, each covering only a small area of 6.5 square metres, to collect data painstakingly with pen and paper. It took one person an average of 30 minutes to scout these three sampling points on each land parcel. The whole scouting period took 7 to 10 days, which was so laborious that farm owners were struggling to hire enough field workers. Another problem was that the small sample size might result in a biased figure for the number of healthy cotton seedlings per unit of ground. Hence, water and fertiliser management measures taken on this basis could be mistaken, leaving farm owners with lower crop yields in the long run.

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Picture 10. Individual cotton seedling were identified on digital fields map of Lihua Cotton Farm

The introduction of the SAS system has provided a perfect scouting plan for Lihui Cotton Farm which was affected by excess labour, time wasted and inaccurate data collection. XMission has replaced field workers to conduct effective aerial scans of entire fields two to three metres above the crops. It can capture field data of 100 hectares in just one day, ten times more efficient than the classical scouting approach. After image stitching and map processing, XAI identified the shape of individual plants and circled each cotton seedling with 99.98 percent accuracy in the SAS system. For those areas with good seedling population, a moderate increase in water and fertiliser was justified to provide adequate nutritional intake and avoid cotton boll shedding. XAG Agricultural UAS can conduct variable rate fertiliser application using its JetSeed™ granule spreading technology. As for areas below standard, gap filling was implemented in a timely way to ensure optimal plant density.

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Picture 11. Farm owner expecting a bumper harvest of cotton

Compared with previous years, the cotton fields sown with seeds this season have seen a 12.7 percent increase in seedling emergence rate, equivalent to improving final crop yield by USD 13 per hectare. AI software and autonomous hardware systems successfully work in synergy to reduce labour costs while closing the yield gap.

4.2 Lessons learned from implementation of the practice

Building digital farming infrastructure is a priority to implement the pilot scheme of the XAG smart agriculture system in Lihua Cotton Farm, consisting of three major elements: high definition field maps; a high accuracy navigation network such as RTK; and IoT sensing devices such as cameras and weather stations. This is considered an essential path to digitalise the whole farming process and enable smart operation of the agricultural AI platform that can only be developed with a large amount of multidimensional farm data.

The development of agriculture AI must be supported by the science of agronomy, horticulture and plant biology. Technically, every stage of crop growth behaviour is first recognised and encoded into algorithms that optimise the crop models of different plant species. However, farm owners have expressed their concerns over how the application of big data and AI can help them improve crop yield in a sustainable and profitable way. The AI cloud computing platform can effectively analyse field images and identify problems such as lower seedling population, pest diseases and weed invasion. This information will be of no value to farmers if they do not have the right tools to execute AI-driven decision-making.

According to You Chuncheng, Director of the XAG smart farm project: “On the one hand we need to apply intelligent agricultural production equipment adapted to farmers’ needs, including the agricultural drones for autonomous seeding, fertiliser spreading, and crop spraying, as well as the survey drone and IoT devices that can rapidly capture field conditions and digitise the farm profile. On the other hand, we also need to adopt scientific crop cultivation methods and build AI analysis models based on crop growth key indicators. This combines precision hardware and software to bridge the gap between perception, diagnosis, decision-making and execution.”

5. Economic, social and environmental impacts

5.1 Advancing agricultural productivity

The realisation of AI in agriculture has bridged the gap between accurate perception of field conditions and execution of best farming practices. A large amount of farmland data are collected to feed the AI engine which empowers farmers with smart decisions while supporting precision operations to improve farm productivity and profitability. In China, with the expanding network of RTK base infrastructure, XAG has collected field data on 8.9 million hectares that cover 28 provinces and 906 cities or counties, as well as introducing over 51 000 agricultural drones into China’s rural areas. Up to 31 August 2020, nearly 8.7 million farming households have benefited from XAG’s smart agriculture solutions on field mapping, precision seeding, fertilisation, and crop protection. A large-scale commercial application of unmanned devices is now underway to transform China’s agriculture.

With agriculture AI to automate the field scouting process, farm owners can allocate agricultural resources more effectively, via the SAS system, to regulate crop growth, control pest diseases and increase soil fertility. XAG has mobilised its partners and service providers to serve 40 million hectares of farmland with smart agtech, contributing to a total increase in crop yield of 3 490 000 tonnes. Farming labour costs have also been substantially reduced while removing occupational health risks for field workers.

5.2 Reducing environmental footprints

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Picture 12. XAG drones, guided by artificial intelligence prescription map, reseed an area degraded by overgrazing in Sichuan, China

With the help of XAI to analyse plant growth and discern abnormalities over entire land plots, the operational accuracy of autonomous drones and robots reaches a new high. This is helping farmers avoid misuse or overuse of agrochemicals and agricultural water to make China's farming system more aligned with the UN Sustainable Development Goals. Since 2017, XAG together with its partners, have cut the use of pesticides and fertilisers by 22 100 tonnes and conserved 5.09 million tonnes of water. Replacing diesel tractors with AI-powered electric drones, XAG has also cut 368 063 tonnes of carbon dioxide emissions as an active response to climate change. For instance, XAG leveraged its drone seeding technology, based on AI prescription maps, to recover a 700 hectare degraded pasture farm in Ruoergai Grasslands, one of China's three largest wetlands.

5.3 Promoting a sustainable countryside

As one of the most cutting edge technologies built upon highly sophisticated algorithms, AI plays an important role in reversing the aging crisis and improving farmers' livelihoods. XAG's smart agriculture system is tackling the stigma around farming as a career. With the opportunity to engage with high tech, more and more young people are attracted back to their hometown, injecting a vigorous, elite workforce into rural development. This helps redistribute resources and talents to reduce inequality between rural and urban areas.

During the process of scaling up agriculture AI, XAG collaborates with external business partners, including financial institutions, agrochemical businesses and government agencies, to offer value-added services based on agricultural big data. Under national data protection rules, insurance companies and financial institutions can now quantify each farm's agricultural productivity and build an individual credit risk system for farmers through the farming data shared by XAG. Chinese smallholders thereby have equal access to loans and claims at lower costs.

© XAG

Picture 13. The tech-savvy young farmers

Section 6. Innovation and success factors

Peng Bin, founder of XAG, argued that the XAG smart agriculture system has been running for almost two years and already shown its effect in advancing farm productivity. "If we integrate big data, AI and precise execution by unmanned vehicles, we can not only discover problems early but also help farmers solve their problems directly, significantly transforming China's smallholder economy and promoting the diffusion of smart agriculture."

AI is not a single technological entity. The successful take-off of agriculture AI in farm management largely lies in its cohesive integration with different technologies, including drones, robots, use of the internet and ICT (information communication technologies). Through development of integrated hardware and software solutions, XAG has created a closed loop smart agriculture ecosystem, where AI can harness the power of big data and autonomous devices to achieve a multiplier effect. Field maps, crop images and environmental data are captured in bulk to facilitate XAI deep learning analysis which provides agronomic guidance for high precision operations. Drones and robots automatically record and upload operational data, such as flight speed, spray volume, coverage and trajectory in the SAS system to train AI to become smarter.

Apart from technological innovation, urbanisation, consumption upgrades and policy support are three external engines driving the scale up of agriculture AI in China. The past two decades have seen an increasing shortage of rural labour which has pushed traditional farming systems to the brink of collapse, while stimulating an urgent demand for intelligent technologies like AI that bring flexibility to farms of all sizes. As fast economic growth catalyses consumption upgrades, urban consumer demand for high quality food without pesticide residue has in turn encouraged farmers to improve their production methods. Traditional agricultural production that is blind, crude, and inefficient has been gradually phased out and replaced by efficient, low consumption and sustainable technology.

7. The potential scalability of an AI farm

Since the commercial launch of SAS, an increasing number of family-run and corporate farms across China, like Lihua Cotton Industry, have imported the whole series of XAG hardware and software to enable new style farming. Though China's agricultural economy is still dominated by small-scale farming, rural land circulation has been gaining momentum in recent years to enable smart agricultural management on a moderate scale. According to the National Bureau of Statistics, the land circulation rate in Chinese rural areas has significantly increased from 5.2 percent in 2007 to nearly 40 percent in 2018, when 35 million hectares of contracted farmland changed ownership. This is expected to hit 60 percent by 2025, indicating an emergent trend of technological intensive cultivation with higher demand for the sustainable, efficient AI tool to manage larger farmland.

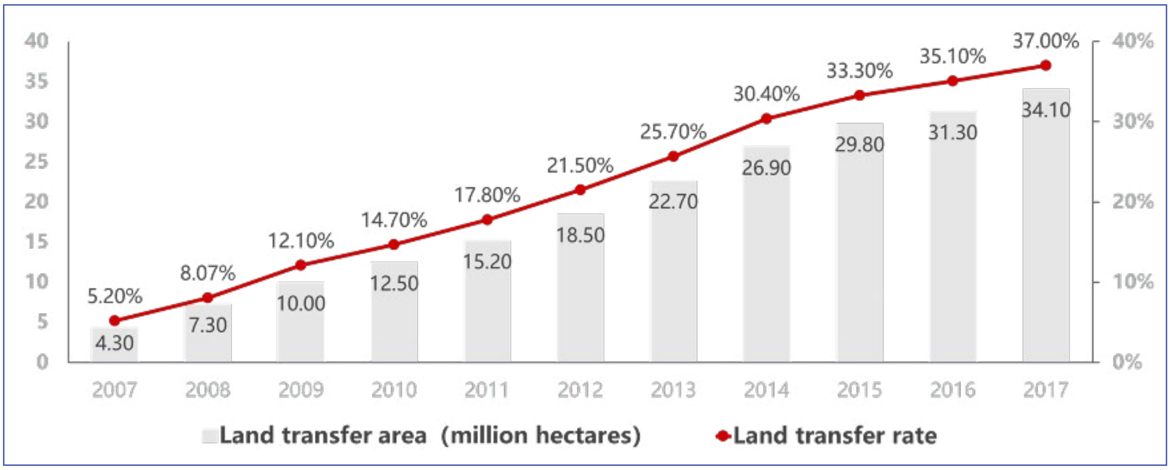

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Figure 10. Accelerating land transfer anticipates a scale up of agriculture artificial intelligence in farm production

XAG has foreseen a rapid AI scale up to accelerate the development of modern agriculture in China. There are 3 million family run farms, farmers' cooperatives and corporate owned farms in need of AI-based smart agriculture solutions, equivalent to a huge potential market scale estimated at USD 110 billion. As new technology takes root and brings empowerment to rural areas, agriculture is heralding unprecedent innovations to become the new core of China's economy.

Though this disruptive integrated solution is an inevitable trend for China's agricultural revolution, the barriers to scale up the new model throughout China remain relatively high. Introducing an integrated SAS is a complicated, long-term project with high upfront costs. It first requires digital infrastructure and field electrification, where many rural areas in China still lag behind.

Family-run farms and farmers' cooperatives form the backbone of the country's agricultural production, but they have limited access to financial services and are very sensitive to input costs. To make smart agriculture solutions more accessible to these target groups, there is a new urgency to break down the walls and build bridges between different stakeholders in the agriculture sector. XAG has been collaborating with governments, investors and other agribusiness in China to build digital farming infrastructure that paves the way for standardised remote operation of agricultural equipment. Smallholders in rural areas who do not have their own ICT tools can order drones and robots from their local service providers to implement various types of fieldwork. In addition, XAG also partnered with some of the largest financial institutions to help establish individual credit risk systems based on farmers' agricultural production data collected by drones and robots. In this way, farmers can obtain loans and financial support at a lower cost.

While the AI-powered smart farm model is solving issues in China, there are great opportunities for its replication in other countries in other parts of world, especially South-east Asia, Latin America and Africa. Farmers in these regions are mostly smallholders who face similar challenges to those in China, due to climate change, rising labour costs and farmland degradation. Many of them grow high value specialty crops such as grapes, blueberries, coffee beans and cocoa on a small scale, to be sold around the world, but they lack nimble, flexible smart devices as well as the SAS system to effectively manage their farms. As XAG has begun expanding its operations globally, government regulation and market education are two important factors to facilitate successful adoption of smart agriculture solutions. Instead of directly selling its technologies and products to local farmers, XAG will work closely with local government to remove the barriers to using drones and robots in agriculture, while training local young people to become the next generation farmers who can scale up the solutions in accordance with their own culture.

Using Alibaba Cloud's AI and Alibaba's ecosystem resource to support the digitization of agriculture in Yanliang

Zeng Zhenyu, Alibaba

FOCUS
The solution offers evidence-based recommendations on soil, watering, fertilizing and harvesting. It has been used to support melon farmers in Yanliang, a district in Xi'an, China.

Alibaba Cloud, the data intelligence backbone of Alibaba Group, has been working on industry-wide intelligent solutions to foster the digital transformation of different sectors, including agriculture, covering plantations, fisheries and forestry. The cloud-based digital solution includes tools powered by the latest technologies in analytics intelligence, AI (artificial intelligence) and machine learning, such as real time analysis, deep neural networks, visual and speech AI, cognitive perception and reasoning, offering valuable insight-driven intelligence for farmers and farming institutes to reap the benefit of e-agriculture.

With accumulated technologies in e-agriculture, Alibaba Cloud has established a proprietary intelligent agriculture platform. The platform can visually display and categorize important elements (such as farm humidity and the number of particular types of produce) throughout the production process in a digital format and provide algorithm-based farming recommendations every step of the management lifecycle from preparing the soil, watering, fertilizing to harvesting.

By applying the Alibaba cloud intelligent agriculture platform we supported farmers in Yanliang (阎良), a district in Xi'an (西安), China, to grow local melons（甜瓜). Melon is the major revenue source for farmers in Yanliang and the harvest can reach 200 000 tonnes per year.

Context

Xi'an local government approached Alibaba Cloud in April 2018, hoping to receive support for local agriculture business through the use of digital technologies. Colleagues from Alibaba Cloud and Tmall, Alibaba's B2C retail platform, visited the Yanliang district in Xi'an and had in-depth discussions with the local farmer association (阎良国强瓜菜专业合作社). The team managed to identify the farmers' pain points quickly: they could only rely on their previous experience growing melons, with no technology at their disposal to enhance product value and market competitiveness.

After consultation with local agriculture experts, Alibaba Cloud leveraged its agriculture intelligent platform and developed tailored digital solutions in June 2018 to support Yanliang farmers to grow and sell their melons in a more scientific, consistent and profitable way. Several business units in Alibaba's ecosystem – including Alibaba Cloud, Tmall, Taobao (Alibaba's C2C retail platform), Ant Financial, (the digital payment solution provider in Alibaba's ecosystem), Cainiao (the logistics provider in Alibaba's ecosystem), Ele.me (the local service provider in Alibaba's ecosystem) – became involved in late 2018 to provide more resource support. As a result, Alibaba formed a partnership with the Xi'an Government to further the collaboration with all the support needed to help Yanliang farmers go digital.

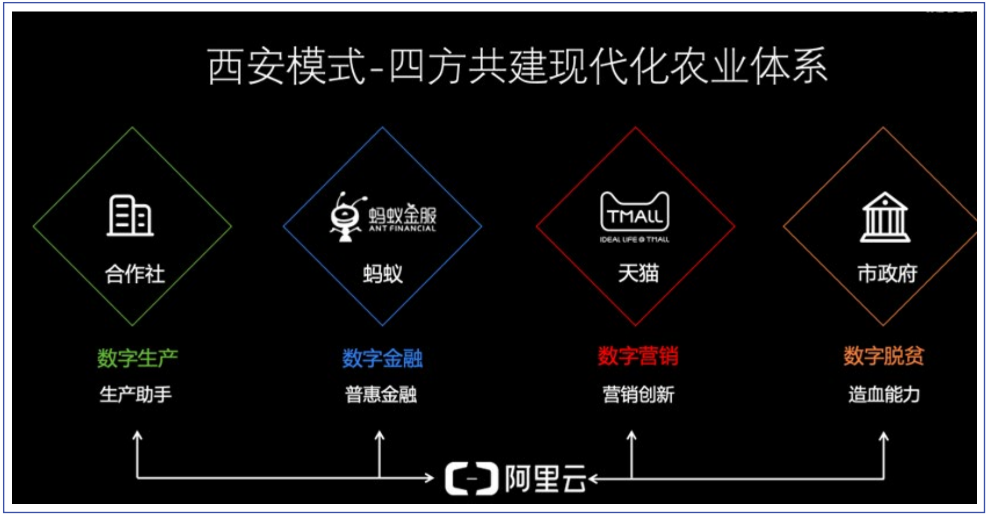

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Figure 11. The Xi'an Yanliang collaboration model

The Yanliang Farmer Association offers direct support to local farmers, Ant Financial provides finance, Tmall offers digital sales and marketing support, Alibaba Cloud provides its agriculture intelligent platform and the Xi'an Government leads poverty alleviation policymaking.

© Alibaba

Picture 14. Sales of Yanliang melons by various merchants on Alibaba's Tmall and Taobao retail platforms

As the partnership develops, Alibaba is not only supporting the melon farmers, but also those who grow kiwis, apricots, pomegranates etc. in Yanliang.

Methodology

Technologies applied in this case include the following.

1. **Digitization of the production process**: Leveraging the cameras installed in the Yanliang farms, we helped local farmers collect key information including temperature, humidity, illumination and the growth status of melons. The information will then be input into Alibaba Cloud's intelligent agriculture platform, making the entire production procedure more digitalized and transparent.

2. **Agriculture intelligence platform to assist every step of the farming lifecycle:** In addition to displaying a visual overview of the farm, Alibaba Cloud's intelligent agriculture platform also categorizes the assets in different subgroups (for example, how many melons are mature enough to be harvested each day and how many need more light exposure). The platform also employs algorithms to recognize the sweetness of the melon through visual AI – identifying the sweetness level of different types of melon from their particular grain patterns. The algorithm can also predict the approximate melon harvest size and date by considering all the variables.

   The Yanliang Farmer Association can access real time updates of the entire production chain and farmers can receive recommendations on watering, fertilization, pollination along every step, from soil condition, seeding, transplanting, flowering to fruit bearing via an app on their mobile phone that syncs up with the Alibaba Cloud's intelligent agriculture platform. Farmers have better control of melons' overall growth, producing market-popular melons without injecting a human-made hormone. Farmers can expect better returns selling products that are more environmentally friendly in a cost effective way, while consumers can enjoy safe, better quality food.

Alibaba Cloud also partners with Ant Financial, the digital payment arm of Alibaba Group, Taobao and Tmall, Alibaba's online retail platforms, Freshippo, Alibaba's new retail supermarket, Cainiao and Ele.me, the logistics platform of Alibaba. All of these can provide farmers with finance options, online and offline sales channels as well as logistics services. By leveraging the resource of Alibaba's ecosystem, we support local farmers from produce growth, harvesting, logistics, marketing and sales to financial support, offering a comprehensive package to make e-agriculture achievable and sustainable.

Figure 12. The Alibaba Cloud agriculture intelligence platform visually displays the lifecycle management of melon growth.

Figure 13. Yanliang Farmer Association uses Alibaba Cloud technology to present an overview of produce growth at Yanliang.

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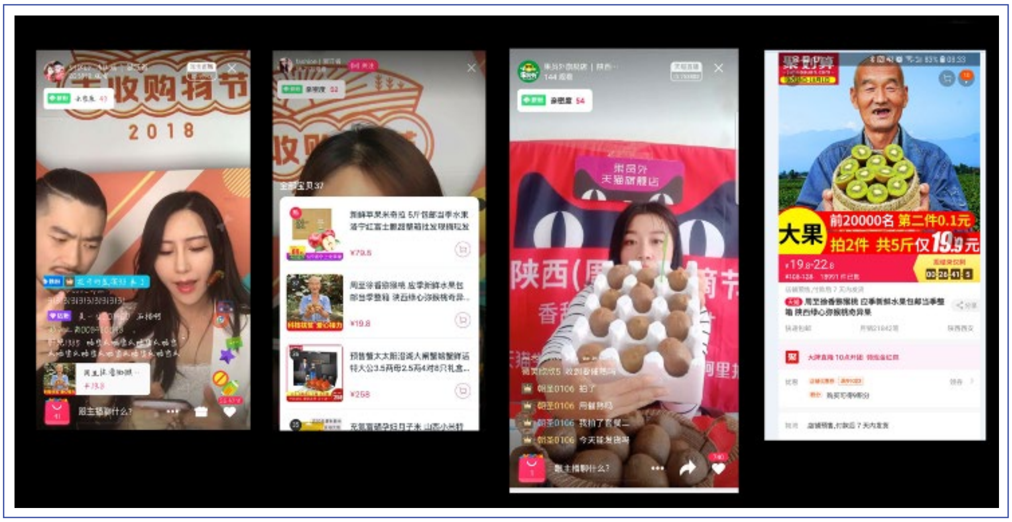
Picture 15. Consumers can turn on the image search on Alibaba's Taobao to download a photo of a melon with an artificial intelligence-based assessment of its sweetness.



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Picture 16. Taobao used its livestreaming services to help Yanliang farmers sell their produce to millions of consumers in China.

Impact

By leveraging Alibaba Cloud's agriculture intelligence platform, farmers can now grow their melons in a more digitalized way that is safer, more environmentally friendly and meets market demand effectively. With the support of technology and digital sales tools, the price of melons raised by Yanliang farmers is normally higher than other types of melons in the market and are loved by consumers, who are willing to pay a higher price for safe, better quality and environmentally friendly produce.

Yanliang farmers also expect higher sales of their melons on Alibaba's various retail channels. In general, sales on Taobao and Tmall increased by over 30 percent compared to the same season in previous years, while the price of a melon increased to close to RMB 5 per pound (454 g) on average, twice the price of a typical melon on the market. A case in point to show the popularity of the Yanliang melon: when it first appeared on Alibaba's Tmall platform during the Alibaba Global Shopping Festival on 11 November 2018 over 3.5 tonnes of melons were sold within 15 minutes. Today, Alibaba Cloud's technology has been applied to over 1.7 million square metres of melon farm sites.

Our thinking

We understand that farmers in many countries, including China, usually have very limited bargaining power in the market. With the help of digital technologies, farmers can now increase the price of their produce thanks to the digital system that makes the entire production process more efficient, safe, transparent, sustainable and environmentally friendly. Farmers can also leverage various digital tools for e-commerce sales to significantly increase their market exposure, connecting with consumers directly to enhance product awareness in a more cost effective way. Embracing digital technologies and intelligent tools opens up many more opportunities for farmers in Yanliang, giving them more competitiveness and bargaining power in the market.

We supported farmers to sell their melons on Alibaba's e-commerce platforms including the C2C platform Taobao and B2C platform Tmall. The underlying technologies of the two retail platforms include personalization, intelligent recommendation and digital marketing, backed by Alibaba's AI and data-driven technologies.

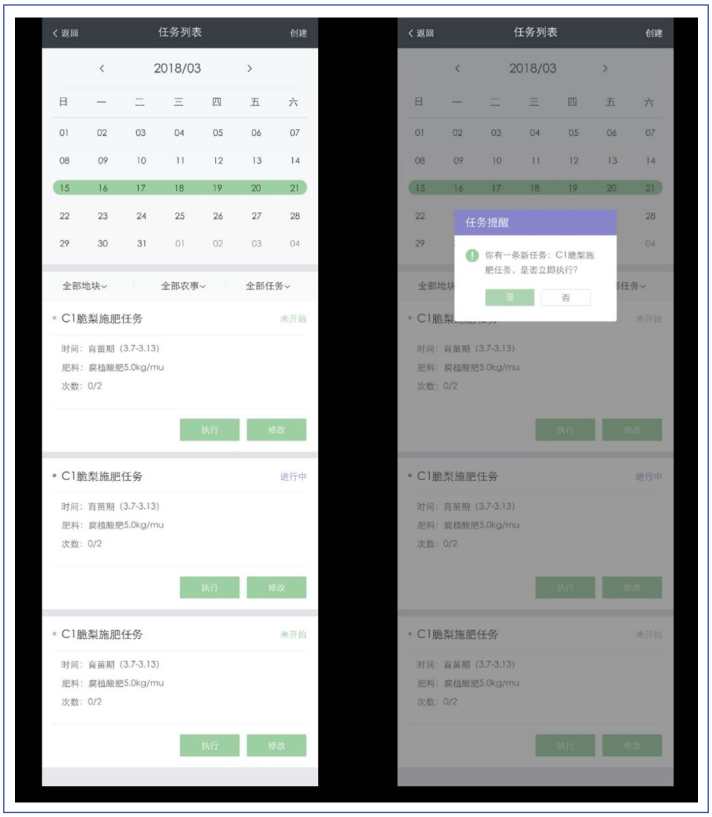
Innovation and success factors

We think a number of key differentiators have led to this success:

1) First of all, our accumulated technology in AI and cloud computing, the backbone of Alibaba Cloud's agriculture intelligence platform, provides the essential foundation that makes the farming management lifecycle – from production to harvesting – digitalized, manageable, standardized, transparent, scientific and efficient.

   Farmers also receive farming tips from the app that we develop together with our IT (information technology) partners. For example, farmers may receive advice on water melons at a particular time of day. They do not need to be digitally savvy and can operate and manage the process very easily by following the algorithm-based standard practice. The melon quality is more consistent, as every melon is of similar size, colour, grain patterns and sweetness, ensuring farmers can deliver a quality melon and maintain a stable revenue.

2) We provide comprehensive resource support from the Alibaba ecosystem – Alibaba Cloud, Ant Technology (previously Ant Financial), Tmall, Taobao, Ele.me, Cainiao – from digital technology, financing, sales and marketing to logistics. The comprehensive and diverse nature of Alibaba's ecosystem resource makes it easy for farmers to see the positive outcome as well: how many orders are placed online, how many viewers are watching the livestream and first hand comments and feedback from consumers are all shown directly on Alibaba's retail platforms. With such tangible benefits, Yanliang farmers are more enthusiastic and convinced about using digital tools to upgrade their farming practices.



Picture 17. The application interface: task alerts are sent every day to farmers to remind them about all the necessary steps during the production management lifecycle.

© Alibaba

Picture 18. Consumers' positive comments left on the retail platform

Constraints

1) While the technology itself is mature, it cannot change the macro environment. Agriculture relies heavily on weather and climate change, so the volume of produce can fluctuate greatly. During abnormal weather, AI could not do much to alter the situation. For example, melon sweetness might drop due to more rainy days.

   AI can forecast the impact of abnormal weather on products and offer suggestions on how to change farming practices to lessen the impact. For example, Alibaba Cloud's agriculture intelligence platform might suggest postponing the harvest date till the sweetness of the melon reaches a level acceptable to the market.

2) Another typical challenge is gathering the necessary data for digitization of production. Since most Yanliang melons are grown outdoors, not in the usual glasshouse, it is not easy to gather various indexes, such as temperature and humidity, without proper equipment and cameras installed at the farms. This is especially true when considering expanding the model to other types of produce and rolling it out later in other cities and provinces. Installing the right digital infrastructure at farms, seeking input from farmers, agriculture experts and local farmer associations on how to best protect produce while setting up the equipment are also essential and pivotal.

3) Alibaba Cloud provided not only the platform but also technology support for local deployment. But we also need support to integrate our platform with the IT system of the local farmer association. There were several rounds of discussion and technology testing but Alibaba Cloud took the lead in developing and deploying the intelligent platform, so as not to present too many challenges for local farmers adopting the system.

We believe that to further leverage digital technology to enhance the growth progress and harvesting of farm produce, we need to improve digital infrastructure on the farm, as well as to keep enhancing our algorithms with input from local farmers, to reflect uncertainties such as extended rainy weather to offer valuable in time response.

Lessons learned

We learned a lot during the implementation phase. While digital technology is an undeniable trend in upgrading agriculture, local farmers usually have limited knowledge of how it actually works and what they can expect from it. For example, some farmers were hesitant to install sensors around their farm, concerned the equipment might hinder the natural growth of melons. Others remained unconvinced about following farming tips or were reluctant to record their activities in the daily log.

To convince local farmers we work extensively with the Yanliang Farmer Association and agriculture experts to host regular workshops and training sessions, explaining how the system works, how AI-based recommendations will affect their usual practices and why it is important to use digital technologies and digital sales to increase production.

We also conducted a pilot test at some selected sites to show the real results to farmers. It took time, patience, and several rounds of communicating with local farmers to educate them, but once they grasped the benefits, farmers were on board quickly and showed great enthusiasm for learning and keeping themselves digitally trained. That is also why we were able to expand the partnership later to cover other types of agriculture products (kiwi, apricots and pomegranates etc.) and by receiving constant feedback from farmers and the Yanliang Farmer Association, we can keep fine-turning our algorithms and improving our agriculture intelligence platform, adding more value to the platform we provided.

Sustainability

The collaboration receives tremendous support from the Xi'an Government and Yanliang Farmer Association who are responsible for the purchase of the AI-based digital solution. Use of the tool by Yanliang farmers is free.

As the Alibaba Cloud agriculture intelligence platform proposed a scientific, environmentally friendly and sustainable model for Yanliang farmers to grow their melons, we do not foresee any negative impacts socially or environmentally.

Most of the project funding comes from the local farmer association, which it used to support the purchase of IT including the Alibaba Cloud agriculture intelligence platform. The Xi'an Government has shown its support and provided some initial funding. The whole model is therefore much more self-sustainable from the start.

Replicability

The technology is mature and the Alibaba Cloud agriculture intelligence platform can be applied to manage other types of farm produce and rolled out in other cities/provinces as well. In the meantime, we need to work closely with local farmers to identify the exact locations for gathering information, where to set up cameras and sensors on-site and adjust our algorithms promptly to reflect on the ground factors, including unpredictable elements like sudden weather change, as we continue our efforts to implement digital technologies and tools locally to achieve the desired results.

The collaboration model with the entire Alibaba ecosystem, from cloud, financing, marketing and sales to logistics, provides a great reference to replicate its success in other cities. The enriched digital offering backed by Alibaba's dedicated resources play an essential role in making the model successful, and we aim to leverage our unique advantage, from advanced technology to rich ecosystem, to enable more farmers to reap the real benefits of digital innovation.

The platform has already been used in overseas markets such as Malaysia. Below is a case study.

Atilze is a Malaysian-based technology company that provides IoT services and cloud applications to customers mainly those in the agriculture sector. Using the Alibaba Cloud agriculture intelligence platform since 2018, the company has provided the latest smart agriculture services and solutions to farmers across Malaysia and the region. These new technologies and solutions have revived the agriculture industry while it transitions from the traditional mode of farming to precision farming. Today, farmers can monitor and control farming parameters using available analytics on the cloud, leading to an increased yield as well as better quality produce.

"By using Atilze sensor hub solution on Alibaba Cloud, farmers can achieve a better income with improved production yields of more than 20 percent. On top of that, it can reduce the daily operation costs with real time updates and notification from the cloud," said Tan Han Wei, Head of IoT of Atilze.

Testimony

Xing Guoqiang, Manager of the Yanliang Farmer Association, said: "Our farmers can follow the recommended practices suggested by the Alibaba Cloud agriculture intelligence platform, to ensure the quality of every melon – for example, every melon has similar size and colour, and therefore, our farmers can enjoy better sales of the melon at the market."

Machine learning as a service for farm produce demand forecasting at Foodlocker

Olufemi Aiki, Foodlocker

FOCUS
Solution support demand forecasting for chicken to minimise revenue risks for both farmers and distributers; used in Africa

Context

Foodlocker often runs out of stock of essential protein (chicken). While customers were willing to buy, supply was always a challenge. Initially, we set up production programmes for smallholder farmers but they often could not meet the demand due to lower bird weights (yields), side-selling, and demand fluctuations. We observed that certain patterns existed for demand and by understanding those patterns we could better serve our customers without running out of stock or overstocking.

Methodology

We looked at the application of time series demand data forecasting as an approach to determining potential future demand for protein. Our approach took us into the world of machine learning and deep learning where we applied multilinear perception, long/short-term memory, convoluted neural networks, ARIMA, SARIMA, exponential smoothening, etc. as methods of running predictions.

How it works. We collect historical time series demand data from a large buyer of farm produce e.g. chicken, soybeans, etc. and via our algorithms, split the dataset into training and testing datasets. With the training dataset, the model is trained (learning) and with the testing dataset, it is validated through walk-forward validation, generating a predictive accuracy indication through error terms. If the error terms are unacceptable, hyperparameter tuning (via gridsearch) is used to obtain more appropriate hyperparameters and/or other models are used to achieve better predictive accuracy.

We then run predictions through our dedicated machines using the tested model. Our initial work did not include hyperparameter tuning but to obtain more accurate results, we included it. Hence, a typical user need not be machine or deep-learning savvy to be able to use the solution.

Ultimately, every execution of the predictive algorithms churns out single or multistep predictions with error terms that indicate predictive accuracy for the uploaded dataset.

Users of our solution include Foodlocker's analysts, procurement managers of large agricultural produce buyers, data analysts who support procurement or management in decision-making, farm production managers, project managers who work with clusters of farmers, investors, risk-sharers, bankers etc. The solution works like an online calculator and allows users forecast demand or prices based on historical data.

For chicken production, we incentivize farm managers e.g. the real people concept for produce based on the demand information we collected. We use our production management technology at https://www.foodlocker.africa to supervise their activities.

For production, New Hope supplied the feed and we tracked day to day consumption as shown in Figure 14.

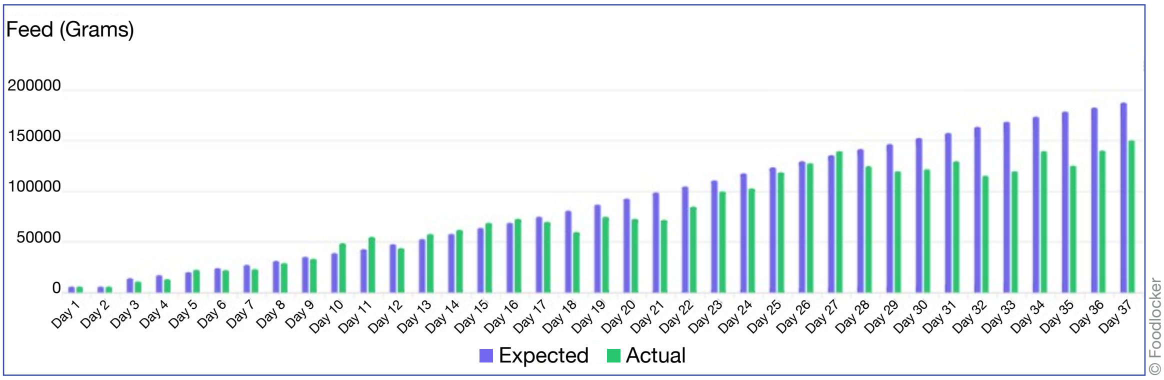


Figure 14. Tracking day to day feed consumption

CHI supplied day old chicks and we tracked the weights of the birds as shown in Figure 15.

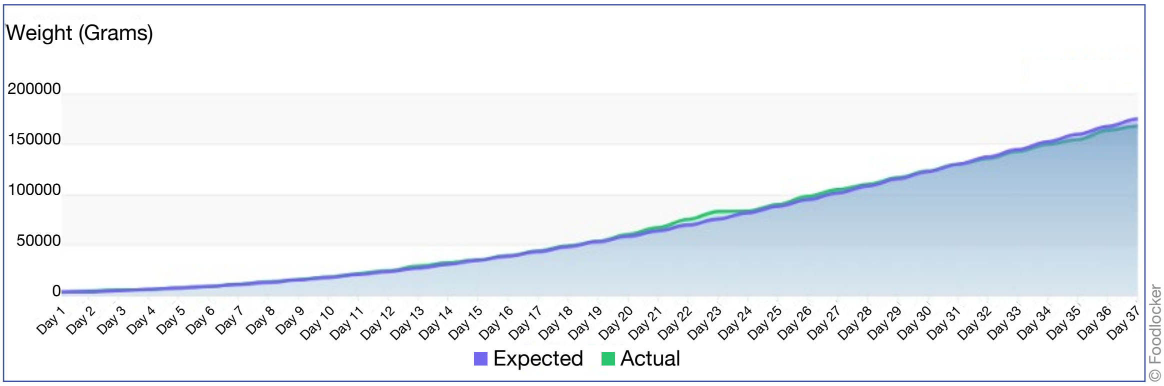


Figure 15. Tracking bird weight

We tracked revenues, cost profile, and margins and obtained the results shown in Figure 16.

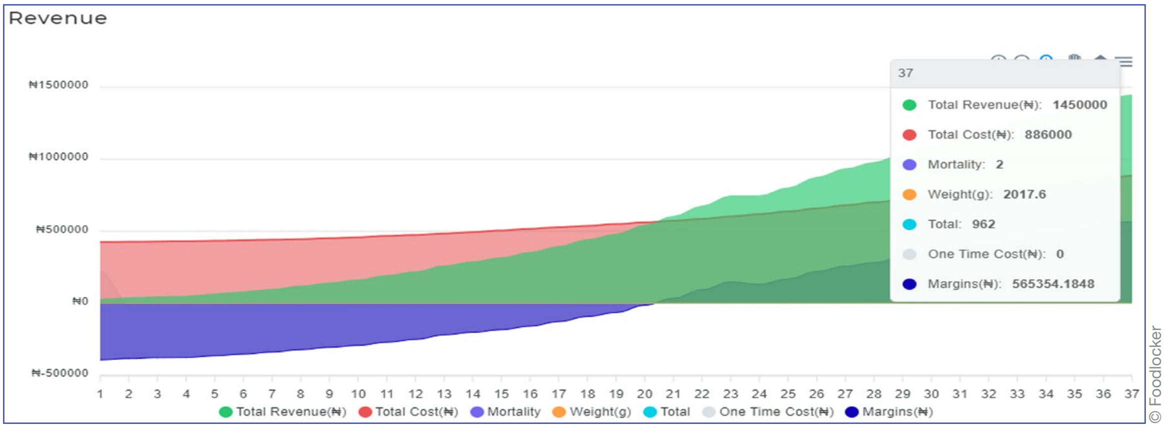


Figure 16. Tracking revenues, cost profile and margins

Support for the demand forecasting solution was through our work at Foodlocker and also provided by a data scientist in Morocco.

Roles and responsibilities

- Demand forecasting is usually done by Foodlocker or an analyst from the large buyer, investor, risk sharer or bank who can use web pages.
- Farmers send daily reports via SMS (short message service) only. Farm cluster managers usually train them in sending reports in their preferred language and nothing more is required from them apart from engaging with their cluster managers and project managers during on board meetings, via SMS or when inspecting their farms.
- Other stakeholders include large buyers, investors, risk sharers or banks who only need to be able to use web pages to understand the progress of projects they are tracking.

Impact

Through the power of demand forecasting, we have seen that losses on farms that work with us reduce to single digits, procurement managers have a better understanding of demand and thus can plan supply/procurement more efficiently, reduce out of stock occurrences significantly and minimize overstocking.

Smallholder farmers who work with us can expect close to 100 percent offtake as all demand data exchanged with them translate into offtake from ready buyers whose historical demand data were used to generate the original predictions.

Our approach also helps us prevent side-selling as many eyes focus on the projects from initiation to maturity. Cluster managers and project managers, who visit farms, are incentivized based on comparing actual yields of each farm with expected and agreed yields.

We have already combined our demand forecasting solution with our production management system at https://www.foodlocker.africa. That combination allows us to communicate the right anticipated demand to smallholder farmers and allows us to cluster those farmers into more effective and efficient production units. They are empowered by project managers and cluster managers who possess a proper grasp of good agricultural practices and can access investors in different agricultural products, all through our https://www.foodlocker.africa platform. We expect to support over 20 000 farmers over the next 5 to 7 years with our end to end solution that interprets demand, sources supply, manages production and reports updates and provides visibility and traceability to multiple stakeholders including lenders, investors, risk sharers, governments and NGOs.

Innovation and success factors

Our practice is successful because it relies on real data from large and retail buyers. If demand fluctuates, we run an omnichannel system key account managers, warehouse stores and e-commerce platform (https://www.foodlocker.com.ng) that helps us divert produce to other channels. Similar practices try to solve the problem of demand forecasting at a scale at which they cannot collect historical data efficiently or successfully. Ours allows us to collect historical data from real and willing buyers. Thus, our forecasts can be validated over time via real patronage that we also control.

We are promoting the solution through engagements with the Nigeria Incentive-Based Risk Sharing System for Agricultural Lending (NIRSAL) for their Agro-Geo Cooperative Finance Scheme and by engaging some aggregators. Foodlocker is also embarking on commercial scale production projects for tomatoes, scotch-bonnet peppers and chicken for some of the large buyers we have already identified and engaged. Smallholder farmers are the major beneficiaries of this approach as they do not have to worry about sourcing inputs, capital, logistics, storage or markets. They come on board through our existing networks of farmers and some third party agents.

Constraints

Some of the challenges we encountered include the lack of sufficiently qualified data science personnel in Nigeria, lack of awareness about the methodologies required, the need for higher capacity computers, unwillingness of some buyers to release historical data etc. External support in recruitment, buying machines and upskilling from machine learning communities have helped a lot.

While most technology solutions for agriculture fall short because they are incomprehensible or too advanced for users, mostly farmers, we have adopted a simplified approach in our design.

The interaction of farmers with our platform can only take place via the daily or periodic reports they send via SMS, in any language, according to a specific format. Before a project commences, cluster managers and project managers will train the farmers on good agricultural practices applicable to that value chain and how to send their SMS reports. They will also be informed about the potential impact of deviating from agreed agricultural practices on yield and on their own outcomes.

Beneficiaries such as buyers, aggregators, procurement managers, investors, risk sharers, banks, etc. only have to be able to access web pages and read charts to understand demand trends and track the progress of their projects as shown in terms of average weight of birds, average height of plants, average number of fruits per plant etc. For the kind of buyers we target, that is usually not a problem.

Lessons learned

No one model will be good enough for all datasets, produce types or seasons. It is important to work with an ensemble of models and to adopt hyperparameter tuning in order to produce more accurate forecasts. Also, fluctuations or excessive disturbances driven by Black Swan events such as COVID-19 may still arise. Hence, it will be necessary to shore up demand or create alternative demand streams to guarantee produce flow from farms to buyers and thus limit revenue risk.

It is vitally important to track production progress daily and provide means for farmers to send notifications when things go wrong. Also, cluster managers are advised to visit each farm under their care once a week for as long as the project lasts. They also send pictures showing evidence of progress on each farm to https://www.foodlocker.africa. In that way, we can cross-reference virtual data with physical inspection.

Sustainability

Our solution is sustainable and farmers need not buy the solution. They only need to sign on as farmers at https://www.foodlocker.africa to benefit from the AI (artificial intelligence) solution, production management and support infrastructure. It is the job of our analysts at Foodlocker, project sponsors, buyers, project managers to interpret, understand and communicate the data to smallholder farmers in terms of demand ready supply requirements/targets. The solution has no negative impact on the environment and because everything is tracked we can influence the choice of agrochemicals, promote organic production options, etc. as well as enforce responsible sourcing and prevention of child labour. The marginal cost of executing the solution will remain close to zero as it is entirely a software solution. The input is data, the processing is done via algorithms and the output is data.

Replicability

The practice is very replicable across multiple produce types within the agricultural value chain. We have implemented the approach with chicken and scotch-bonnet peppers while tomato production is about to start. We only need demand data from large buyers of different produce types to be able to run forecasts on them. For larger scale projects, we need to engage with a number of farm produce buyers e.g. Cargill, Chicken Republic, KFC, Olam, Barry Callebaut, Nestlé, Dangote Tomato Processing Factory, GB Foods and collect historical data from them to run demand forecasts and secure supplies from smallholder farmers for them.

AI-powered field robots for smallholder farmers in Fiji and Samoa

Salah Sukkareih (University of Sydney), Aggeris

FOCUS
An AI solution to help operate a robotic platform that can perform a range of functions to facilitate farming activities; piloted in Fiji and Samoa

Context

The Australian Centre for Field Robotics (ACFR) at the University of Sydney has been conducting research and development in AI (artificial intelligence) and agriculture robotics for over ten years with one of the solutions being the digital farmhand. It was trialled among smallholder farmers in Australia and Indonesia when in 2017 the ACFR received funding from the Australian Government Department of Foreign Affairs and Trade's (DFAT) innovationXchange (iXc) to undertake a pilot project to explore how the digital farmhand could assist smallholder farmers in the Pacific Island nations of Fiji and Samoa. The objective was to understand how the technology could be used to improve their agricultural productivity and in turn their food and nutrition security and what are the limitations or constraints in introducing this technology. Professor Salah Sukkarieh led the project which was initiated through the LAUNCH Food Grants Programme.

During the project our team encountered a number of farming challenges that the Pacific Islander community faces that would strongly support the introduction and use of an AI-powered digital farmhand:

- low farm labour productivity which can improve with a mobile electric platform to operate continuously and intelligently based on AI techniques for the guidance system for row following;
- lack of affordable chemical inputs indicating that AI technology can reduce the amount of chemical inputs used when coupled with intelligent spraying;
- the damaging impact of weeds, pests and crop disease which continue to hamper access to quality food for the vast majority of the population. This can be dealt with using AI techniques with sensing capability to intelligently activate weeding and spraying tools.

In order to deliver the project outcomes, the key focus, in addition to demonstrating the physical platform, was on the development and deployment of AI technology since the types of farms and crops are different from those previously encountered.

Methodology

Three on-farm trials and one workshop were held in each country. In Fiji these were on 18-21 June 2018 and in Samoa on 13-16 August 2018.

Prior to these field trips, our team had adjusted the digital farmhand to incorporate several new design features that could potentially improve its functionality on farms in the Pacific Islands. These were identified during the pre-trial visits to Fiji and Samoa in March 2018 and to Fiji in August 2017 for the InnovationXchange launch event. The new design features included:

- ability to easily change the width of the platform – this allows the digital farmhand the flexibility to operate on crop rows of different configurations and adjust the sensing placement for the AI solutions;
- higher crop clearance – this allows the platform to collect data on taller, more mature crops;
- more powerful motors for improved speed and torque performance allowing the digital farmhand to operate on uneven terrain or soft soil, as well as give it the ability to tow heavier implements, in particular those that are to be actuated intelligently based on the AI algorithms;
- additional plant sensing modalities – these assist in gathering more in-field data for analysis and to feed data to the AI techniques.

At the field trials our team outlined the project's objectives to the growers and demonstrated how digital farmhand works. These included using the spraying, seeding and weeding implements on the available crop rows as well as collecting crop data using a digital farmhand's camera and demonstrating the capability of the crop intelligence solutions that worked off machine learning techniques.

The digital farmhand performed extremely well throughout the field trials in Fiji and Samoa and confirmed that these design changes had been crucial to its success. In both countries, our team was able to quickly deploy the platform onto vegetable rows to collect data and test implements. In some instances, it was reconfigured several times on the same farm.

Different business models and subsets of digital farmhand's platform that may be of interest to farmers were also explored, e.g. smart spraying systems based on AI crop and weed intelligence solutions that are manually carried or handheld sensing systems for data collection for the AI digital agronomy solutions. Assessing the economic viability of the sensing, algorithms and digital farmhand is a key next step towards making the technology available to farmers.

Growers were extremely positive about the possibilities of using digital farmhand on their farms and spoke to the team at length about their respective farm operations.

Workshop attendees included growers, extension officers and local agricultural business representatives. Breakdown of attendees between countries is:

- Fiji (16) – 9 men and 7 women
- Samoa (21) – 8 men and 13 women.

Impact

Growers who attended the on-farm trials provided valuable information about their farming systems, sale of produce and the challenges they face. Data for a range of crops, including the commonly grown crops of tomato, eggplant and cabbage, were collected for future data analytics work especially to develop AI solutions that could be used to determine crop yield and health. Workshop discussions focused on challenges for growers and how subsets of the digital farmhand platform could address these.

The feminisation of agriculture calls for a greater use of technology to support on-farm physical tasks. Given the modularity of the digital farmhand platform there was a lot of positive feedback, especially from the female attendees at the workshops in both Fiji and Samoa, that it would be a very welcome addition to their farming operation. In particular we noticed that having the ability to digitise agronomy, e.g. machine learning systems that can determine crop yield and health, would support these farmers by providing real time information they would not be able to obtain because of their limited access to agronomy advice. This we felt would be a significant advance on current practices.

In general, the response from all who attended the on-farm trials and workshops was overwhelmingly positive and they were eager for the next steps towards introduction of the system. Farmers felt there was a great need for such a platform to assist them with the many challenges they face, seeing both the physical and digital advantage that an AI robotic tool would provide.

Innovation and success factors

The pilot project was successful in that it achieved its goal of establishing the foundations of an introduction of the digital farmhand to the Pacific Islands. Key innovation and success factors included the following.

- Education: We have outlined a training programme to be implemented via a local organisation and modularised to allow different levels of training for end-users. Workshop surveys showed the need for continuous support to use the technology and maintain robotic equipment, supporting the establishment of a local organisation to provide hands on training and support. Key findings around AI included how a community could be taught to train machine learning algorithms that are provided, not the development of the AI solutions. This would allow for the continuous update of the machine learning models to deal with changes in the environment such as the identification of new pests or new crops planted.

- ICT: Our research into ICT (information communication technologies) showed that network coverage in the project area was wide and excellent, although the level of desktop and laptop computing power was limited. One of the key innovations we demonstrated was using mobile phones as both a sensor capturing device as well as a computation platform for the AI solutions. This demonstrated the use of an ubiquitous piece of technology known as an AI holder of the algorithms.

- Trials and workshops: The key finding from the field trials and workshops was that using subsets of the digital farmhand technology would be most beneficial to the majority of smallholder farmers in Fiji and Samoa. For example, farm workers will often apply chemicals inconsistently so a smart sprayer powered by AI and sensing was discussed at the workshop. Farm maps collected with a mobile phone can be used to identify the areas of a paddock that need water, fertiliser, herbicide or pesticide based on a GPS (global positioning satellite) location. A sprayer carried by a farm worker could be programmed to turn on and off based on information from the farm map as well as what is detected in the field based on the machine learning models. This would increase the effectiveness and precision of the chemicals applied, which would in turn reduce the amount used unnecessarily. This reduction in chemicals is both an environmental and economic benefit to the farmers.

The biggest challenges farmer organisations are working to resolve are the lack of soil testing and farmer knowledge needed to identify pests, diseases and nutrient deficiencies in crops. Insect pest scouting, along with seeding, was listed as the most useful task for a robot to perform in the workshop survey responses received (63 percent of responses). Extension officers regularly visit farms, with each farmer typically visited fortnightly. These visits provide a scalable system for collecting data via photos taken with smartphones. These data could be sent to our team for processing and analysis, using the AI solutions, concerning pests, diseases and nutrient deficiencies, as is currently done with smallholder farmers in Australia. Results will be provided back to the extension officers to communicate to farmers. The widely available 4G mobile network makes solutions such as this possible.

- Economic sustainability: A number of different business model options for introducing the digital farmhand to Fiji and Samoa were formulated. The most likely is a service model, being viewed as the most sustainable. As part of the service model, a commercial entity would be set up in-country and a consultant(s) employed to work with local growers, offering the services of the digital farmhand for a set fee or a share of profits gained by overall improvement in quality and yield, as well as reduction in input costs.

  In this model the platform would be designed, built and supplied by an Australian entity (recently established as Agerris Pty Ltd) that will also either provide service in the Pacific Islands or train the employees of the in-country entity to provide the service. From a sustainability perspective, the in-country entity would be similar to a social enterprise, training locals in the operation and effective use of the robot. This way the local entity can demonstrate it is a committed partner in the production process in the short term and could eventually evolve to be a sales or distribution point in the long term.

  A service model, initially, provides the opportunity to change the mindset of growers towards the use of technology as well as helping reduce the cost of technology to potentially more affordable levels. The aim is to work directly with the keenest growers and partners at first. These are the people who will eventually encourage others to become involved and then help shape the agenda in their respective communities regarding the use of on-farm technology going forward.

Constraints

- From a financial cost/benefit perspective, our analysis relied on grower approximations as published gross margin budgets were found to be unrealistic. Financial information was communicated to us through email, verbal discussions and in survey responses. Based on this we took an average view across relatively similar farming operations.

- Gaining an understanding of how to build a support network around smallholder farmers to include maintenance of the platform, education and appropriate ICT systems, access to affordable lending products so that they have access to the technology, etc. This will be key to implement the AI solution on a wide scale across different farms and crop types.

Lessons learned

- Subsets of the digital farmhand such as the AI-powered smart spraying systems carried manually or handheld sensing systems for data collection for post-processed AI techniques, would be useful to growers. This is especially important in Samoa where flexible tools are needed to accommodate the wider variety of farm layouts and the typically smaller size of farms.

- The identification of pests and diseases is a major challenge for growers and a key candidate for AI powered crop analytics applications that the digital farmhand can provide in Fiji and Samoa.

- Economics analysis showed that a service business model is the most sustainable solution for introducing the digital farmhand into Fiji and Samoa. A service model provides the opportunity for growers to access the technology via local consultants for a fee or share of profits. Initially working with the keenest growers, the service model also allows demonstration of the technology benefits to the wider agricultural community. This could be both for the robotic solution as well as the AI-powered crop analytics.

- ICT and education system analysis indicate that establishing a local organisation that works directly with end-users on farms is the most effective method of delivering training to support the use of the digital farmhand – both for the physical platform as well as the AI crop intelligence solutions. The training programme must be suitable for a wide range of potential applications of the technology and be applicable to users with little or no understanding of sensing, robotics or AI.

- Direct contact with growers through the field trials, workshops and interviews provided the ACFR team with invaluable information regarding farming operations and their associated challenges in Fiji and Samoa.

- The digital farmhand demonstrations using the physical platform as well as the AI crop analytic solutions on crop rows was found to be the most effective method of explaining how the technology works, as well as the most appropriate time to gather feedback. Further demonstrations, as well as quantifying any economic benefit from its use, will be instrumental in securing the support of the agricultural community in the future.

- The workshops were an important element in communicating the purpose of the project. Surveys confirmed that all respondents had a better understanding of the potential uses of robotics on farms after participating in the workshops.

- Gaining information to support an economic model was challenging due to a lack of reliable published farm production data and record keeping on the part of growers. Our interaction with local organisations and interviews and surveys with growers themselves were extremely valuable and provided the information used for economic analysis.

Sustainability

Discussions with growers during on-farm trials and workshops revealed an openness to new technology as long as it translates to increased crop sales. The digital farmhand, for example, is of interest if it can seed, weed and precision spray, potentially increasing crop yield, reducing crop variability and crop mortality.

Delivering on the demand for local produce has not always been possible as input costs are high, traditional production methods are still in use and expensive to maintain sustainably and access to finance for agriculture is very limited.

Lending products are often inappropriate for agriculture with high interest rates, which in turn restricts on-farm investment. High vulnerability to natural disasters such as cyclones, droughts and rising sea level, as well as increasing pests and diseases also contribute to the challenging environment most growers face.

However, due to agriculture's recognized potential, many growers are embracing technology as a way of introducing new and niche crops into their operations as well as trying to improve the quality and supply consistency of the crops they currently plant. The Pacific Islands have long been a favoured tourist destination in the region and with increased tourism comes a greater requirement for locally grown organic produce of the highest quality. In this context the economic and environmental sustainability of agricultural production in Fiji and Samoa is imperative as it will in turn support long-term economic growth.

For the majority of farmers, a service model whereby a contractor would use digital farmhand to provide physical on-farm services or the AI solutions delivering crop intelligence to growers was found to be the most sustainable initially. A service offering would allow growers to access the technology via local consultants. Initially working with the keenest growers, the service model also allows demonstration of the technology benefits to the wider agricultural community. Furthermore, the opportunity for establishing microwork activities to benefit the whole community was also apparent.

Replicability

The main conclusion from this pilot project was that the cost of the digital farmhand should be reduced for smallholders to access it through a service. Given the original idea of building the platform in-country did not add up economically, we have since established an Australian entity (Agerris) that will build the digital farmhand and export it to in-country entities in the Pacific Islands to begin providing the service to smallholder farmers.

Testimony

Ricky Westerlund is one of Samoa's largest commercial vegetable growers. His 45-acre farm is the leading supplier of vegetables to hospitals, hotels, restaurants and markets in Samoa. Taking over from his father, his farm has been in intensive operation for generations.

Ricky was very interested and excited about the prospect of having the digital farmhand as part of his farming operations. The modularity of the platform and its ability to precision spray were very appealing to him. He was quoted as saying: "If you do it with a machine it will be the same every time. Spraying is an expensive business. If a person sprays these rows one hour a week maybe 20 Tala a week for spraying. If you spray over four weeks, you're already at 80 Tala, plus your irrigation. All this adds up to an expensive trip to market."

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Picture 19. Digital farmhand spraying crops in Fiji (University of Sydney)

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Picture 20. Discussing the capability of the digital farmhand with local farmers (University of Sydney)

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Picture 21. Workshop with local farmers (University of Sydney)

Using AI technology to convert the condition of plant body into data

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FOCUS
An AI-enabled melon grading system to automate the inspection of melon quality and reduce labour intensity of the process. Initial tests conducted in Japan indicate feasability but further research and development are required to make the system operational.

Context

Daiwa Computer Co. is an IT (information technology) company established in 1977. The main focus of our company is to design and develop core business software. In 2009 we launched into the field of agriculture in order to change traditional agriculture, whereby intuition and experience account for about 70 percent of data-based agriculture. Since the decline of Japanese agriculture began to be seen as a problem, we considered that ICT (information communication technologies) could support new, successful entrants into agriculture.

We contacted many farmers and asked for their cooperation to introduce technology from various angles to illustrate the potential of ICT in agriculture. Then we met a farmer growing earls melons in Fukuroi-shi, Shizuoka Prefecture and signed a contract with him to introduce different technologies to use ICT in agriculture, applying them to melon cultivation.

In 2012 we also launched our own farm with more applied cases of ICT technology, such as environment control technology and recording work hours on a farm.

Here, we introduce an experiment to use AI (artificial intelligence) when judging melon grades.

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Methods

We consider that AI could check the condition of plant bodies and so have focused on grading melons.

One of the ranking criteria of melons is their beautiful appearance including condition (uniformity, extent of reticulation rising, etc.) of net (reticulation on the epidermis of melons), shape of the ball, and the length of the antenna (T-shaped vine at the head of the melon). Those that do not meet product criteria, such as blemishes, are excluded and others ranked according to quality of appearance. There are four grades, in descending order of quality: Fuji (which means Mt Fuji); Yama (which means mountain); Shiro (which means white); Yuki (which means snow).

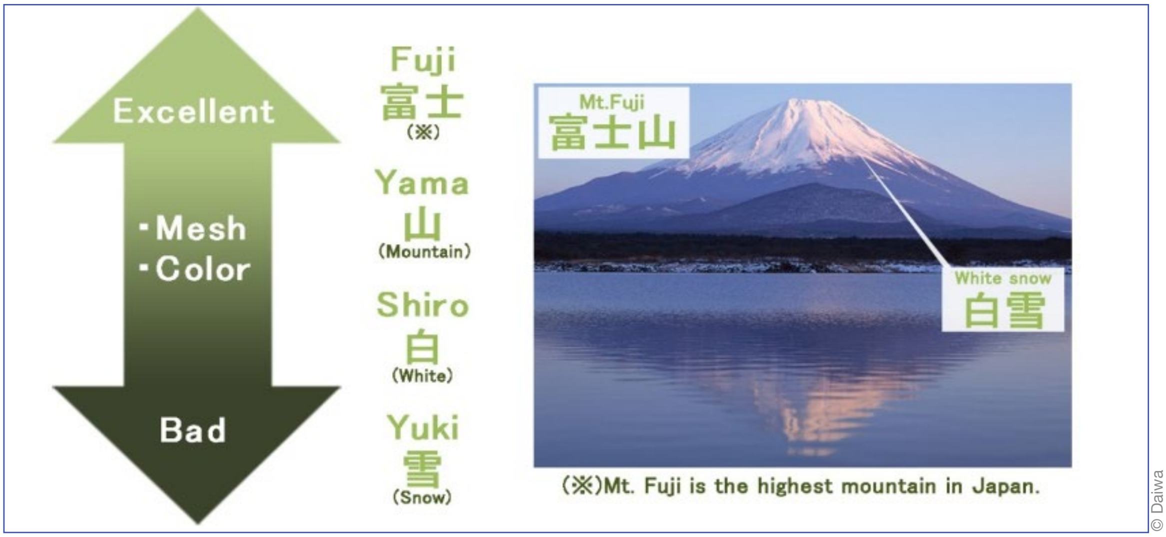


Figure 17. The four grades of melon quality

This grading is a standard for quality assurance, the melons being judged by skilled farmers and through unannounced inspection at the shipping location. The grading is based on specialist experience and there are no numerical values. Consequently, it is difficult particularly for new entrants to conduct the evaluation. We considered the possibility of absolute grading through standardized judgment using AI and conducted proof of concept (PoC), which also served as a technology investigation for the image categorization technique.

We carried out the following experiment, though we are not specialists in using AI. Please be aware it may contain some incorrect approaches or knowledge.

Since we do not specialize in AI we used trial and error alongside expert partners. The specialist said we can grade adequately using images, so we started to gather these and other materials, using the techniques he shared with us to construct a trained AI model.

The goal for this experiment was to make it possible for anyone to classify melons as specialists do using AR (augmented reality) glasses, assisted by AI technology. We have tried to gain more efficiency without modifying the work procedure, adding to the work or increasing the burden on the operator.

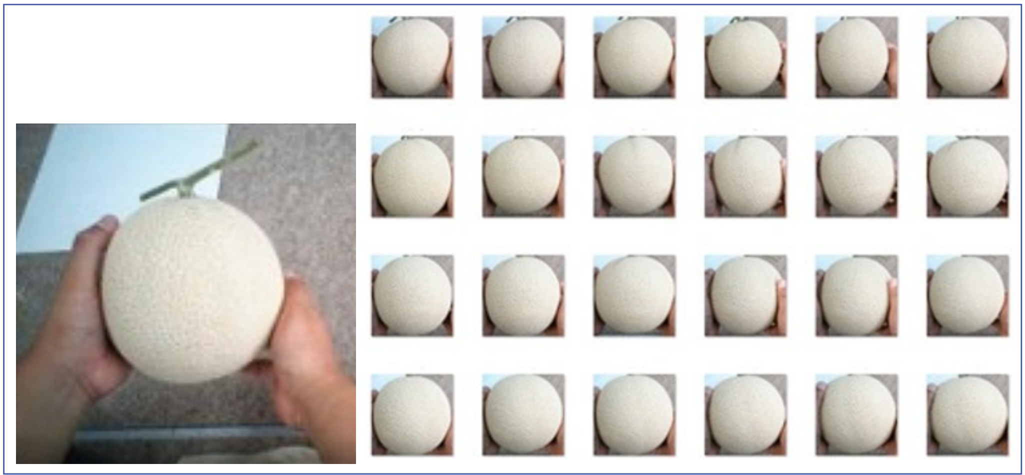
In the grading criteria Fuji indicates excellent, usually applied to less than 1 percent of produce, Yama is good, Shiro is common and Yuki means poor. However, for this experiment, to establish absolute grade values, we assigned five steps to the grade classification standards A-E with Yama and Shiro each separated into two steps, A and B plus C and D with Yuki designated as E.

First, we collected images of the melons for PoC. Film of the products from our own farm was recorded for every grade and image data extracted and labelled. The image data required careful filming and aimed to ensure ample and uniform data. Therefore, we shot movies at a special location using a general digital camera to prepare image data.

Since melons are generally spherical, people usually judge them by looking at them from different angles while rotating them in their hands. To reproduce the procedure, we shot image data from different angles, without giving information about the angle.

We supplied the specialist with the image data and asked him to create a model while carrying out the grade classification test. He reported he obtained a certain level of correct answers in classification using an existing object detection model. We confirmed that by using the model supplied (Ver. 1 model), grading can take place with a certain degree of accuracy using melons we had not supplied at the first filming. When we focused only on the net, we ensured with the Ver. 1 model that AI can classify with a certain degree of accuracy.

Next, we filmed with AR glasses, mimicking the live environment while extracting the images.



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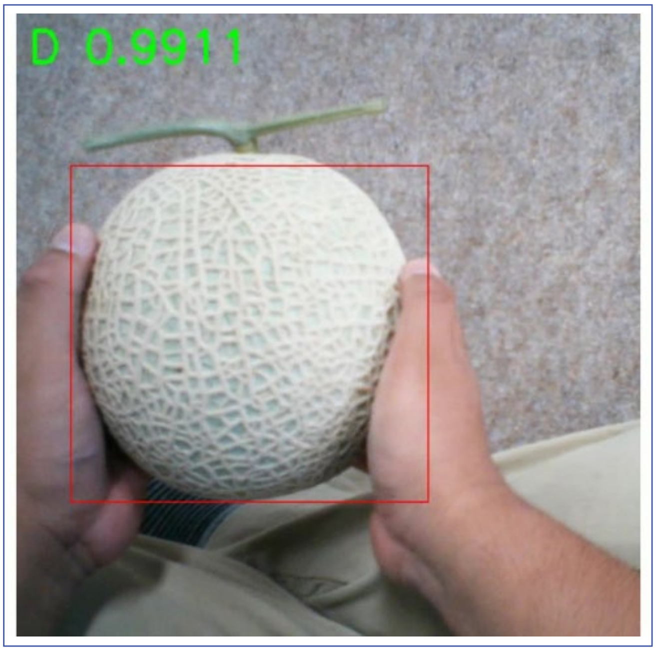
Picture 22. Using artificial intelligence filming techniques to grade melons

The results of classification by the Ver. 1 model with the obtained images showed low accuracy and unavailability for actual use. This is because the images were too diverse from those used to create Ver. 1.

In addition to the performance of the camera equipped with AR glasses, the high-speed visual contact created blurring in most of the images derived from the filming. Even in correctly extracted photographs, saturation, brightness and colour quality changed in different shooting environments. We found that judgment when using the Ver. 1 model was unsatisfactory.

We then developed the Ver. 2 model based on the images recorded using AR glasses. To standardize the image data, we adjusted the shooting environment, for example, blocking sunlight as far as possible and using fluorescent light and auxiliary light. We retrieved new image data from the recordings and labelled them and again prepared a trained model.

After completing Ver. 2, we confirmed that using these images the model can classify, with relatively high accuracy, data on all the melons, even those excluded from grading. However, we found there was varied accuracy for those melons shot under conditions other than those of the Ver. 2 model. We prepared Ver. 3 and Ver. 4 shooting models, but accuracy did not improve significantly. Accurate classification became possible for the images used to create the model but there was no improved accuracy using different models. While preparing Ver. 3 and Ver. 4, we detected a pattern. The following is an example of the results of the analysis, shown as an image using AR glasses.



Picture 23. Analysis results shown as an image using augmented reality glasses

We finally realized that human grading of melons is highly relative.

Melons are harvested at 90 to 120 days after planting and we harvest melons 2-3 times per month throughout the year in seven connected greenhouses on our farm.

The image data were prepared at the time of harvesting but each set of image data from Ver. 1 to Ver. 4 were taken from different parts of the harvest. In the same harvest crop, the classification was highly accurate, but using different lots the accuracy drops. Results also varied when using multiple versions for a single melon. For example, an image using the Ver. 2 model was judged as A but as B using the Ver. 3 model.

We presume there is a different classification standard between models. The reason is that with human grading, the operator to some extent implicitly sets their own relative standards against every other sample being assessed with no absolute index for evaluation.

Human evaluation and classification are relative. Harvesting is seasonal and there are errors due to varieties. The centre lines for each standard of classification change with each harvest. It does seem possible to evaluate without seasonal distortion and errors due to assessing different varieties by using Ver.2 as standard.

From this experiment, we conclude that evaluation of melon grading can be done by filming and using trained models. We do need to improve for PoC and suggest four possible improvements.

1. Data should be collected throughout the year with grading divided into ten classification levels.
2. Image data recorded should be in various forms in terms of brightness, viewing angle etc. using image processing techniques.
3. Accompanying information group for evaluation should be assembled in advance and acquired concurrently with the photo shooting.
4. The information should be continuously updated, with new systems to improve the accuracy of the model.

By achieving this it is possible to grade more accurately than humans can with better crop appearance and a consistent level of quality without any seasonal variations, benefiting both producers and sellers. Although there may be some variation depending on the models, by connecting to AR glasses as PoC, we concluded an experiment that indicates the grade of the melon in the person's hand. As a result, we now strongly believe in the future of AI in agriculture.

These PoCs enable companies who do not specialize in AI to fully utilize analysis/categorization techniques using image data since clearly AI classification is superior to that of humans. We then considered whether the judging points involved in the index of cultivation could be extracted from images of a plant body during growth and have initiated a new investigation in collaboration with a college and relevant organizations. Classification of a plant body at each growth stage by calculating the correlation between its condition and the amount of photosynthesis from images would be an effective and very useful index for farmers.

If the condition of a plant body can be visualized in real time using AR glasses and MR (mixed reality) glasses, farmers will be better able to check the condition of the plant, even when not physically present. These indicators can be applied not only to melons but to other crops.

When introducing ICT technology into agriculture, a major problem is converting the plant body into data.

In facility horticulture, environmental control to promote photosynthesis is based on environmental data including temperature, humidity, sunlight and precipitation, with automatic, sensor controlled irrigation. However, the condition of the plant body influencing these controls has not yet been converted into data.

Observation is necessary but it is always subjective. Even under a controlled environment, it takes a long time to reflect changes in the plant and it can be difficult to distinguish between cause and effect. If we can continuously convert the plant body into data, it would solve this problem to some extent.

We consider that using image categorization with AI is the first step in converting a plant body into data. It will allow us to promote agriculture that makes extensive use of data, saving work and increasing productivity. Particularly in Japan, with a decline in the working population, agriculture needs technological innovation over the next 20 years to achieve further labour savings. To achieve a more neo-futuristic agriculture, we will continue to challenge from different perspectives such as creation of indices using AI technology and visualising the condition of plant bodies.

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