ABSTRACT

In 2017, the Council of Agriculture in Taiwan initiated “Smart Agriculture (SA)”, a 6-year research program. Based on sensor/sensing technologies, intelligent robots, Internet of Things (IoTs) and big data analytics, it is expected to build smart production, marketing and digital service systems locally to efficiently enhance the whole agricultural productivity and capacity. In addition, it is anticipated to build an active, all-purpose agricultural consumption/service platform to integrate important information and technical resources in agriculture, fishery and livestock to facilitate the convenient usage of data and digital service, thus increasing customer’s trust on food safety. In the SA program, especially, a common information platform (CIP) which uses the Open Application Programming Interface (Open API) to connect with a range of existing application databases has been established. Two applications of the CIP to foster data-driven agriculture in the future are being developed and presented in this paper. First, the collection of the production and management data will be used to analyze and predict the production capacity of every farm in each relevant region. These results of analysis and prediction will then become the basis for production decision-making. Besides, utilization of big data analytic technology embedded in the CIP has generated some expert group decision models. These models will not only provide decision-making advices for agricultural production management, but also establish integrated application models of agricultural value chain. ‘DIGITAL TWIN’ (DT) module applied in the agricultural facilities (such as greenhouse) for tomato/cucumber in Taiwan is an example of such decision model, and possesses 3F characteristics: Footprint, Fingerprint, and Forecast. The ‘Footprint (digital footprint)’ is meant to collect relevant data from sensors in the greenhouse and actuators of farmer’s operation. The ‘Fingerprint’ is meant to establish predictive models (feature) by learning different digital footprints from outstanding farmers or farming experts. Furthermore, the ‘Forecast’ is meant to conduct adaptive decision-making based on the control suggestion derived by comparing real time sensors data with fingerprints. Second, by providing a consumer-oriented production model and constructing a cross-channel between production and marketing, a digital service system has been established. With information services taking machine-readable, format-open, interface-indexing and machine-writable into consideration, a mechanism based on open application interface program is established to provide services for farmers, agricultural enterprises and system developers. For example, a common agricultural consumption/service platform is implemented to connect the supply chain of agricultural produce (food) between farmers and consumers. At present, traceable food safety information services given by ‘FOOD SAFETY SITUATION ROOM (FSSR)’ module has been applied for campus lunches in more than 3,000 primary and secondary schools through big data exchange mechanism. The mechanism can
establish a traceability food chain management between the origins and schools, and provide more immediate and convenient information for food safety. As a result, the risk and reaction time of food safety incident will be reduced, thus increasing the trust of all stakeholders on food safety.

Keywords: Smart agriculture, common information platform, data driven agriculture, digital twin, food safety situation room

INTRODUCTION

According to IBM’s ‘What is big data?’, 90% of the data in the world were generated over the last two years alone. Tens of thousands data sets were created by sensors, mobile phones and numerous IoT devices every day. In agriculture, more and more agri-data (such as weather, soil, sensors, and marketing) and informatics (such as plant disease and pest control knowhow) are used to improve and increase the capacity and efficiency of production. Pricewaterhouse Coopers (PwC, 2019) indicated that digitization and smart automation are expected to contribute as much as 14% to global GDP gains by 2030, equivalent to about US$15 trillion in today’s value. As with all industries, technology plays a key role in the operation of the agrifood sector, a US$7.8 trillion industry, responsible for feeding the planet and employing over 40 percent of the global population.

As to the current status of digital technologies in agriculture and rural areas, Trendov et al. (2019) indicated that a booming agriculture bounding in the process of digital transformation is observed. But they found simultaneously how small farmers are not included in this transformation process, thus increasing the digital divide. The first conclusion they reported is related to the lack of systematic and official data regarding rural areas and digital technologies in agriculture. There are only data at the country level, without a greater distinction in rural and urban areas. Second, the difference in terms of economic and social factors between developed and developing countries is concluded, together with the existence of global companies versus those of a local, community or family nature. Lastly, the digital technologies themselves have strong economies of scale and scope. That is to say, digital technologies clearly deliver economic value, as long as they reach the scales and necessary scope.

Most interestingly, the challenge concerned by Trendov et al. is that transformative innovations and modern tools for making agricultural systems more efficient and sustainable are often not designed for smallholder use. Adaptation to smaller scales is a major challenge for smallholder farmers in developing countries. Future works were suggested as follows: (a) to systematize the data associated with the identification of risks, opportunities and gaps in adoption and sustainability of digital technologies in agriculture at the country level, particularly in rural areas; (b) to identify the different models that allow small farmers to join the digital transformation, not only simply amassing more evidence, but also facilitating the leap for smallholder farmers in the ongoing process of digital transformation; and (c) to create a mechanism that synthesizes the art of digital technologies in agriculture with related factors identified in the work, which especially involves further development of a Digital Agriculture Readiness Index concerned by the FAO Regional Office for Europe and Central Asia in 2015.

Through more and more data, several digital agri-services (such as agricultural management system i-PLANT discussed by Tsay et al. (2019)) are generated. Data-driven techniques help boost agricultural productivity by increasing yields, reducing losses and cutting down input costs. However, these techniques have seen sparse adoption owing to high costs of manual data collection and limited connectivity solutions. To address these limitations, Vasisht et al. (2017) develop an end-to-end IoT platform, FarmBeats, for agriculture, which enables seamless data collection from various sensors, cameras and drones. As shown in Figure 1, TV White Spaces radio networking, a low-cost, long range technology, is leveraged to setup a high-bandwidth connection from the farmer’s home to the farm. The weather-aware solar-powered IoT base station at farm provides a Wi-Fi interface for connections between sensors and other devices. Furthermore, the local intelligent gateway siting at the farmer’s home at the other end of the White Spaces link ensures that services are available in the Cloud and offline as well as performs two functions: (a) creates summaries for future use and ships them to the cloud and (b) delivers applications that can be provided locally.
As more and more digital agri-services will be created by this data-driven way, providing more convenient access way or mechanism should be considered in advance. Data scientists spend 80% of their time in obtaining, cleaning, and preparing data, and only 20% of their time in building models, analyzing, visualizing, and drawing conclusions from the data. Therefore, preparing “good” data is more important and should be considered.

COMMON INFORMATION PLATFORM

In order to support and enhance the development of data-driven services in agriculture, a 6-year Smart Agriculture (SA) research program has been initiated by the Council of Agriculture (COA) of Taiwan since 2017 (Figure 2). It incorporates sensor/sensing technology, intelligence robot, internet of things (IoTs) and big data analytics in order to build smart production, marketing and digital service systems to efficiently enhance the whole agricultural productivity and capacity. In the SA program, acting as an active, all-purpose agricultural consumption/service bridge, a Common Information Platform (CIP) is established to support agriculture, fishery and livestock sectors to facilitate the convenient usage of data and digital services. The CIP uses Open Application Programming Interface (Open API) to connect with a range of existing application databases and develop digital services of concern. All programs developed on the CIP will be standardized to be interoperable with sharing of data and information and offer farmers location-specific solutions.

Three main goals of the CIP are Sharing, Service, and Synergy (SSS):

- **Sharing**
  Standards of data exchange and privilege rules for data-sharing among different agri-areas will be established. The collected data will be provided for each other to create innovative, collaborative agri-service to solve the complex agri-problems;

- **Service**
  Heterogeneous data (public data, such as agri-weather, market conditions, pesticide, fertilizer and food safety, as well as private data, such as data from IOT sensors of the agribusiness companies) will be integrated and provided demand-driven services under a clear announcement of the rights and obligations. It also supports free access for academic research, but will be charged for commercial uses in the future; and

- **Synergy**
  The combined power of agri-research institutes, government departments and agribusiness companies are to support agri-innovation. This platform will make it possible to collaborate and cooperate with various agri-experts, agri-ICTs, agri-machinery and sensors.

The structure of agricultural CIP can be divided into three layers from data sources to applications, including data lake, interface, and service layer (As shown in Figure 2). To create the convenient usage of agri-data and agri-digital service, the programs integrating official data and open data such as weather, pesticide, fertilizer, food safety and market information are designed to share every
stakeholder in agriculture by using the Open API mechanism for data exchange. Each third party vendors or research institutes can easily take advantage of the Open API to get agriculture data or digital service they need and develop innovative services to solve all kinds of farmers’ problems.

Figure 2. The structure of agriculture common information platform

At present, the data sources of big data lake of the CIP have four categories, including food safety databases for agricultural and fishery products, meteorological databases, pesticide/fertilizer databases, and market information databases. As shown in Figure 3, the number of data collection on these databases exceeds 100 million records with 37 categorized items, currently. The meteorological data collection is the largest (about 40 million records), the traceability data follow (about 12 million records), and the market data collection is the third (about 10 million records).

Figure 3. The data sources of agriculture common information platform
The method of big data exchange adopts Open API mechanism. To date, totally 56 APIs have been provided. The third parties and research institutes registered for the CIP have exceeded 25 units, and the number of accessing the databases by using the Open API reaches nearly 450,000 times. The highest number of accessing times of the Open APIs is the traceability data of food safety databases for agricultural and fishery products. Due to the Open API mechanism, data could be accessed easily and quickly to create more innovative digital services. Two applications on the CIP to facilitate must-changes for the benefit of smallholder farmers and foster data-driven agriculture has been developed, which are presented in this paper as follows.

**DIGITAL TWIN APPLICATION IN SMART AGRICULTURE**

To date, key point domain knowhow of expert farmers only exists in their brains. Usually, there is no good way to systematize and intellectualize the domain knowhow of concern. IOTs and AI (Artificial Intelligence) are growing rapidly in recent years. By taking advantage of the technologies, there is a good chance to systematically learn and preserve agricultural experiences/knowhow of farmers.

Digital Twin, one of Gartner’s Top 10 Strategic Technology Trends for 2017, is a virtual model driven by real data from physical objectives (such as a component, process, or system). It collects data from sensors of operating environments or systems and uses these data to create simulated models for monitoring certain behaviors or some key components of the systems, thus preventing problems from occurring. For example, General Electric (GE) Company used Digital Twin to monitor the physical/virtual engine and discover the problem of physical engine. In agriculture, expert farmers’ experience and knowhow need transferring to young or new farmers, but the transferring process usually is long and slow. In view of this, the concept of the Digital Twin is firstly applied in greenhouse to analyze, discover and extract the behavior of the expert farmers and correlate with related information from sensor, actuator and crop. By integrating artificial intelligence with human intelligence, a ‘DIGITAL TWIN (DT)’ module embedded in the CIP is therefore developed for data-driven greenhouse farming. Sensors are used to collect situation data under the optimal cultivation controlled by expert farmers, and then the data are analyzed by machine learning’s deep learning techniques to establish the decision-making models of DT that can replicate expert farmers’ experience and knowhow in control strategies. The DT algorithm or module can systematically preserve farmers’ experience and knowhow and control actuators in greenhouse by investigating and utilizing the related information from sensor and crop. The scenario and process of DT is shown in Figure 4.

![Digital Twin Application in Smart Agriculture](image.png)
The proposed DT in greenhouse possesses 3F characteristics (FFF: Footprint, Fingerprint, and Forecast). Firstly, the ‘Footprint (digital footprint)’ is meant to collect relevant data from sensors and actuators of farmer’s operations in greenhouses. IOT sensors and actuators used for digital footprint act correspondingly every five minutes. In this case, there are eight types of sensors such as temperature and moisture of air/soil, EC and pH of soil, luminosity and CO\(_2\). There are four types of actuators such as roof windows, fans, shading-nets and spray system.

The real time data coming from IOT sensors in greenhouses are shown in form of a dashboard (Figure 5). The status of every sensor is shown with the latest six data sets and in a warning mechanism like traffic lights for monitoring the corresponding health situation of sensor. Green words and signs in the dashboard tell that the sensor status is good. However, a red one is telling that something wrong is going on and the farm manager needs to check the sensor in the field.

![The dashboard of the IOT(footprint)](image)

Figure 5. The dashboard of IOT sensors in greenhouses

Secondly, the ‘Fingerprint’ (As shown in Figure 6) is meant to establish predictive (feature) models by learning different digital footprints in terms of operation behaviors, environmental changes and responsive actions from expert farmers. Under the same environment and crop conditions, expert farmers usually will make better decisions on crop farming than general farmers. The DT module is used to observe the conditions of crop and environment under control based on expert farmers’ experience and domain knowhow and figure out the required better control strategy and management. Therefore, different digital twin models (Model 1, Model 2, Model 3,……, Model N) will be extracted and developed from different operating behaviors (action responses) of different expert farmers in greenhouse.
Figure 6. The process of fingerprint in the DT module

Furthermore, the ‘Forecast’ is meant to conduct adaptive decision-making based on the control suggestion derived by comparing real time sensors data with fingerprints. This mechanism has been applied in the agricultural facilities (such as greenhouse) for tomato/cucumber in Taiwan and continuously verified for its performance. According to data from sensors and actuators, the proposed service agent or software will send a real-time decision making advice to the farm manager by using adaptive digital twin models learnt from expert farmers. With this kind of help from digital twin models based on expert farmers’ experience and knowhow, even junior farmers could have better control actions.

As shown in Figure 7, a prototype dashboard of adaptive decision-making recommendation with concerned parameters of three sensors (temperature, humidity and luminance) and four actuators (roof window, fans, shading-nets and spray system) is demonstrated. In the first window, the list of different digital twin models is shown. Every model can be selected by clicking its check box. The details corresponding to the selected model is then displayed as a sensing curve in the second window. It will help the farm managers or expert farmers to understand what the situation is based on the generated curve. In the third and fourth windows, the status of sensing curve based on the selected digital twin model within the duration of 15 minutes before and after the monitoring action is shown respectively. In the fifth window, the temporal sequence of the model building is shown accordingly. It shows the process of discovering and extracting the selected digital twin model at different time periods.
With these digital twin models, the experience and knowhow of expert farmers will be preserved systematically via the CIP and transformed more easily and more efficiently to new generation of young farmers by using mobile application. In Figure 8, the user interactive interface with adaptive decision-making recommendation is implemented on mobile devices. As the environmental condition changes and there is a need to have a control action, the relevant farm managers can receive warning messages via mobile devices. The farm managers can click the message to see the control recommendation. They could accept it directly by push the confirm button or check it further in details by double-clicking. Every recommendation from the digital twin model can be checked for further details and permitted to change if other better control option is available confirmed. However, every control behavior in greenhouse will be recorded to feed back to and optimize the digital twin model.
FOOD SAFETY SITUATION ROOM WITH HETEROGENEOUS DATA

Another data driven application case embedded in the CIP is ‘FOOD SAFETY SITUATION ROOM (FSSR)’ module. Heterogeneous food safety data in terms of traceability data (3 Labels and 1 QR code, 3L1Q) of agricultural and livestock products from Council of Agriculture (COA) and materials used in campus lunch by Ministry of Education are integrated in the CIP (As shown in Figure 8) and offered as the data source of the ‘FSSR’ module.

According to the regulation of food safety, all primary and secondary schools (about 3,000 totally) need to use traceable agriculture and aquaculture products, which is tagged as “3L1Q” in Taiwan. To provide useful data to a Campus Food Ingredients Registration Platform (CFIRP) of the Ministry of Education for national primary and secondary schools, the CIP integrated these heterogeneous data which originally come from several databases of different departments of COA and solved the indispensable data problem related with asynchrony. Therefore, this kind of big data exchange application based on agri-data integration and sharing can help the government to strengthen consumers' trust on food safety.

To ensure safety of campus lunch, the CFIRP of Ministry of Education can get food safety information daily from the CIP via Open API interface. At the same time, the CIP also collects data about the served lunch (such as restaurant, food supplier, county and city of the school) from the CFIRP. By taking advantage of the special feature of Sankey diagram (Figure 10), the ‘FSSR’ module is then designed with interactive data visualizations to monitor the food safety traceability chain.

Figure 9. The data source of ‘FSSR’ module embedded in the CIP

Figure 10. Sankey diagram of the food safety traceability chain for campus lunch

The Sankey diagram is a type of flow diagram, in which the width of the arrows is shown proportionally to the flow quantity. It puts a visual emphasis on the major transfers or flows within a system. It helps locating the dominant contributions to an overall flow. Several parameters such as certification (what kinds of 3L1Q), production location of agri-products, food supplier/company,
school, city and county of the school, and date can be selected in the ‘FSSR’ module (As shown in Figs. 11 & 12).

**Figure 11.** Main parameters about agri-products can be selected in the ‘FSSR’ module

By selecting several different parameters, as shown in Figure 10, the FSSR module can show very clearly that where and when the materials of campus lunch come from and which food companies cook and served the lunch. In other words, all traceable data can be displayed in a variety of ways by Sankey diagram to query different parameters needed. In Figure 10, it also indicates how the Sankey diagram for heterogeneous food safety information works by selecting certification, location of agricultural products, food supplier/company, and county in which the school is located.

Depending on the viewpoint of different stakeholders (such as government officials, teachers...), the order and inclusion of these parameters in the FSSR module can be changed flexibly with a very convenient and friendly interface. For example, the government officials want to secure the food traceability chain of the schools in Yilan County and figure out how many major food suppliers/companies deliver agri-products tagged with TAP (one of the 3L1Q) for campus lunch. As shown in Figure 13, by selecting TAP, all schools in Yilan county and date, the FSSR module can show location...
of the agri-products tagged with TAP, food suppliers and schools in Yilan by Sankey diagram. In this setting, Yizhen Group Food Center is shown to provide most materials for Yilan’s schools and needs to be a targeted object for strengthening counseling and auditing. At the same time, the food suppliers and agri-products at some production areas are also included as counseling objects to prevent food safety scandals.

Figure 13. Sankey diagram of the food safety traceability chain for campus lunch

Another application of the FSSR module is the monitoring of pesticide residue. The alert function for pesticide residue monitoring is also developed in the FSSR module with Sankey diagram. The results of pesticide residue testing for agri-products are integrated in the CIP. If pesticide residue detection is unqualified, the FSSR module will show a red alert on the flow of the Sankey diagram and users can figure out what happened to this food safety chain. The details of unqualified agri-products are shown in Figure 14 that which food company and school are affected and where the agri-products come from. This function will help government officials, teachers, and parents to understand quickly the situation of food safety misconduct and avoid further society panic.

Figure 14. Alert function for pesticide residue monitoring

CONCLUSION

The motivation of SA research program is for innovation in agriculture by using science and technology such as sensor technologies, intelligent devices, IoTs and big data analytics. The CIP plays an important role to integrate and utilize heterogeneous agri-data. It not only provides a key mechanism
(Open API) to third parties for developing agricultural innovative services, but also has two good examples in terms of DIGITAL TWIN and FSSR to implement data driven services.

‘DIGITAL TWIN (DT)’ module for greenhouse farming is built and designed to extract and learn operation behaviors (responding to environment changes and taking actions) of different expert farmers. A dashboard based on an adaptive decision making interface is offered for farm managers to receive warning messages via mobile devices. The module still needs to be verified continually and optimized by collecting more and more data from sensors and actuators in the different agricultural industries or different crops. The module embedded in the CIP is also expected to expand to other agricultural areas such as Orchid, mushroom and seedling industries and thus enhance its impact on saving more and more experts’ knowhow.

The ‘FOOD SAFETY SITUATION ROOM (FSSR)’ module is an efficient and clear way to integrate and transorm heterogeneous food safety information, which can further monitor and reduce the risk and reaction time of food safety incident. By querying on line, the FSSR module provides immediate, transparent school food information to the community, teachers, students, and parents, thus increasing the peace of mind and trust of all stakeholders on campus lunch. It can also supervise the quality of school food and beverage management jointly by combining the campus food safety management system. The CIP not only provides unique entrances (Open APIs) for food safety certifications information from the CFIRP and traceability data of agricultural and livestock products from different agriculture agencies or departments, but also develops a convenient and friendly interface to monitor the food safety chain.

REFERENCES


Verdouw, C.N., J.W. Kruize. 2017. Digital twins in farm management: illustrations from the FIWARE accelerators SmartAgriFood and Fractals. 7th Asian-Australasian Conference on Precision Agriculture


ACKNOWLEDGEMENTS

The authors would like to express appreciation to Dr. Ye-Nu Wan, Professor, National Chung- Hsing University for his review, comments and contribution to this article.

Date submitted: October 29, 2019

Reviewed, edited and uploaded: November 28, 2019