Farming Decision Support Systems with Digital Twin and Internet of Things: A Desiderata

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Abstract

Modern food production is a complex process involving multiple participants and stakeholders, including farmers, distributors, retailers, financial institutions and regulatory agencies. These participants and stakeholders share a common goal: gathering information about the production process so that they can make informed decisions in order to improve productivity and mitigate risks. However, collecting reliable real-time data and perform proper data analytics remain difficult problems, especially in developing countries where most people rely on agriculture. With this paper, we outline the DeSoFa system, a decision support system for agriculture and aquaculture using digital twin and Internet of things technologies. The main aim of DeSoFa is to collect information from the farming process and perform data mining and what-if analysis, in order to support an ecosystem of the above stakeholders in their own decision-making process.

Keyword: smart agriculture, precision agriculture, Internet of things, digital twin, developing countries.

I. Introduction

Living in a modern city like Singapore and getting all our food from supermarkets can sometimes shield us from first-hand experiences of agriculture and aquaculture. In reality, the transformation from seed to harvest and eventually to food on the dining table involves complex processes and long production schedules that are often unpredictable and difficult to manage. For instance, unpredictable weather conditions may disrupt irrigation schedules, resulting in over- or under-irrigation. Sudden growth of algae may deplete oxygen in a fishpond in a very short period of time and cause massive fish deaths. Such operational risks pose significant threat to the financial wellbeing of the farmer, the credit provider, and the insurer.

Modern agriculture and aquaculture require the collaboration of multiple participants and stakeholders, whose rely on the smooth flow of information to make informed decisions. The major participants include the farmer who is the ultimate producer, distributors and retailers who store, package, transport, and market the harvest to the consumer, financial institutions who oversee capital allocation and provide insurance, and regulatory agencies whose mandate is to guard food safety, environmental sustainability, and financial stability. Every participant or stakeholder is interested in learning and monitoring the production process. For example, the farmer wants to track the level of oxygen and antibiotics in the water in order to avoid fish death; banks can use the same data as early warning signs for non-performing loans; regulatory agencies can use the data to assess environmental impact. However, traditional means for collecting and disseminating such information can be costly.

Table 1. Contrast between agricultural practices and social institutions in developed and developing countries.

Area	Item	Developed Countries	Developing Countries
Scale	Production Scale	Large corporations	Small- to medium-sized farms
Infrastructure	Power supply	Usually stable	Often unstable
	Computer networks	Intermittent for remote farms	Intermittent for remote farms
Financial Capital	Mechanized Production	Extensive	Limited
	Level of capital investment	High	Limited
	Availability of financial services (e.g., credit and insurance)	High	Low
Human Capital	Farm management skills	High	Medium to low
	Financial institutions' ability to assess and control risks	High	Medium to low

Making decisions based on outdated information can have severe consequences. A case in point is the recent outbreak of African swine fever in China. The reliance on manual collection and reporting of data, which were slow and (intentionally or not) fiddled with human error[1] [2], led to slow governmental responses and rapid spreading of the virus throughout China in as little as eight months[3]. Dr. Defa Li, Fellow of the Chinese Academy of Engineering and an authoritative figure on animal husbandry, put the estimated economic cost of the pandemic at 1 trillion Yuan[4]. The pandemic also caused significant losses for insurance companies[5].

Utilizing Internet-of-Things (IoT) technologies [1], [2], big data analytics [3], and precise simulation [4]–[6], the next wave of agricultural revolution holds the promise to mitigate the aforementioned operational risks and facilitate information flow [7]–[9]. Nonetheless, deploying such technologies in developing countries in Southeast Asia and around the world faces a series of unique challenges,

[1] https://www.reuters.com/article/us-china-swinefever-reporting-insight/piles-of-pigs-swine-fever-outbreaks-go-unreported-in-rural-china-idUSKCN1R10VQ
[2] https://www.reuters.com/article/us-china-swinefever/china-cracks-down-on-african-swine-fever-reporting-idUSKCN1NQ09P
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[5] https://www.caixinglobal.com/2019-12-12/chinas-insurers-squeal-as-swine-fever-hits-profits-101493551.html

(a) Farmland in the Pearl River Delta

(b) A Pig Farm in Guangdong

Figure 1. Farms in Guangdong, China. (a) shows an aerial photograph of irregular-shaped farms that rely on natural irrigation and simple plastic mulch (instead of more expensive greenhouses). (b) shows a family-owned pig farm with high animal density within simple fences. Photos taken by one of the authors during field trips.

such as the dominance of small and medium-scaled farms, non-standard farm environments, insufficient capital support and lack of sophisticated management. Table 1 contrasts the farming practices and related social institutions in developed countries and those in developing countries. Figure 1 shows the status of some farms in Guangdong, China. We bring to the reader's attention the small scale of the farms and the low-cost constructions utilized by the farmers. While most successful implementations of smart farming and agricultural IoT have been implemented in developed economies, the problems of the developing world are less studied.

In this position paper, we propose a Digital Twin decision-support system for smart farming, which we call DeSoFa. The platform employs new types of sensors to collect information on agricultural and aquacultural production, conducts automatic and interactive data analysis, and supports informed decision making by multiple stakeholders. In order to cater to unique developing-country challenges, the system is designed with the following considerations:

- The system should be flexible enough to adapt to non-standard farm conditions and operate under harsh environments such as unreliable power supply and intermittent network connections.

- The system must be easy to understand, deploy, and maintain, and be dependable even under poor maintenance.
- The system must be low-cost and not become a financial burden.
- The system should support information collection and data fusion, which will facilitate decision making at the levels of individual farmers, financial institutions, and governments.
- The system contributes to national food safety and security through transparency and traceability

In the next section, we will describe the system components and discuss research questions for each component.

II. The System Architecture

The proposed decision support platform aims to standardize farm processes, boost farm productivity, strengthen the control of pests and diseases, and reduce operational risks in agriculture and aquaculture. By the power of machine learning and "what-if" analysis enabled by the digital twin platform, the system can optimize production based on expert knowledge and data collected from the sensors. Furthermore, governments and financial institutions and regulatory agencies can assess and prepare for potential operational and financial risks.

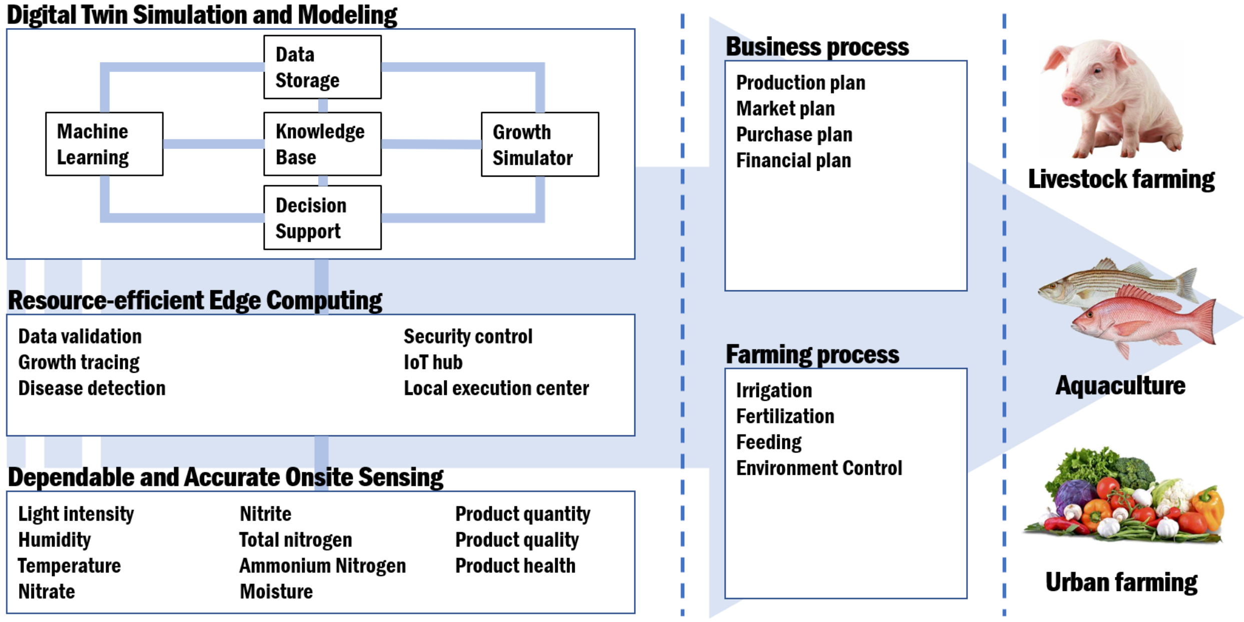

Figure 2. The architecture of the digital twin decision support system for smart farming (DeSoFa) and its position within the ecosystem of stakeholders.

The proposed system supports a wide range of agriculture and aquaculture farming. For example, the platform can help an urban vegetable farm to control its irrigation, fertilization, and environment control systems completely automatically. As a result, the farm can avoid interference of natural environment and human operation errors, resulting in standardized farming operations. In aquaculture, the system can control critical water quality parameters, such as oxygen, eutrophication, and algae growth. Pig farms can identify pigs that exhibit symptoms of African swin fever in real time and respond to them in time.

The proposed system architecture, shown in Figure 2, consists of three major components. First, data on the farm are collected with on-site sensors. After that, the data are processed with edge computing nodes which are low-cost and tolerant of intermittent Internet connections. The collected data enables digital twin simulation and modelling. Finally, the data are analyzed, and the results are aggregated and made available on an open platform supporting an ecosystem, which supports a rich variety of business and farming processes, as well as different types of farms. We describe the research questions in each of the components below.

A. *Dependable and Accurate Onsite Sensing*

This component of the system is responsible for collecting the raw readings, such as audio, visual, and electrochemical signals. We identify the following research questions:

- How do we develop sensors that are self-calibrating and self-verifying?
- How do we accurately estimate maintenance cycles and lifespan of the sensors under varying conditions of farming environments, so that the sensors can be maintained and replaced in time?
- How do we develop accurate sensing technologies that operate under adversarial conditions, such as cameras that can operate under low lighting or low visibility under water?

B. *Resource-efficient Edge Computing*

We aim to develop edge computing technologies that can operate with low power consumption and intermittent network connection. More specifically, we identify the following research questions:

- How do we support cutting-edge machine learning algorithm on affordable and power-efficient hardware?
- How do we verify the collected data in real-time with small computational complexity and low power consumption?
- How do we recognize crops, animals, and fish and assess their quality and quantity via audiovisual signals?
- What kind of network architectures and transmission protocols should we adopt to support reliable communication among heterogeneous sensors and edge computing nodes, when network conditions are unreliable?

C. *Digital Twin Simulation and Modeling*

Digital Twin refers to a class of technologies that create digital replica of the real-world. Within the digital replica, we can conduct fast experimentation and cause-effect analysis, and answer “what-if” questions. In this area, we identify the following research questions:

- How do we build faithful simulations of the real farms at low computational requirements?
- How do we interpolate and extrapolate from the collected data to reason about cause and effect of farming decisions?
- How do we enrich Digital Twin modeling through online learning from heterogeneous data sources?
- When we build a Digital Twin model, how do we tolerate missing data that are inevitable due to unreliable networking conditions and sensor failures without significant performance degradation?
- How do we incorporate external knowledge into Digital Twin modeling? For example, we may represent the external knowledge as knowledge graphs and employ knowledge graph embeddings. Alternatively, external knowledge can be encoded as as prior distributions or constraints in machine learning models.
- How do we evaluate the quality of the Digital Twin models?

IV. Conclusions

The next wave of agriculture revolution will boost agricultural and aquacultural production, improve the efficiency and the sustainability of existing farming practices, and provide stronger guarantees for food safety and financial stability. However, deploying technologies developed in the laboratory in the reality of developing countries remain challenging. In this position paper, we propose a new system-level design for a decision-support system that specifically tackle these challenges and outline related research questions. Due to its advantageous geographical location and central status in global finance, Singapore is uniquely positioned to develop farming and financial solutions with radiating influence to Southeast Asia and rest of the world. We encourage practitioners and researchers in Singapore's IT community to join us in this great endeavor.

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