

Chapter 7

Disrupting Agriculture: The Status and Prospects for AI and Big Data in Smart Agriculture

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ABSTRACT

The United Nations (UN) Food and Agriculture (FAO) estimates that farmers will need to produce about 70% more food by 2050. To accommodate the growing demand, the agricultural industry has grown from labor-intensive to smart agriculture, or Agriculture 4.0, which includes farm equipment that are enhanced using autonomous unmanned decision systems (robotics), big data, and artificial intelligence. In this chapter, the authors conduct a systematic review focusing on big data and artificial intelligence in agriculture. To further guide the literature review process and organize the findings, they devise a framework based on extant literature. The framework is aimed to capture key aspects of agricultural processes, supporting supply chain, key stakeholders with a particular emphasis on the potential, drivers, and challenges of big data and artificial intelligence. They discuss how this new paradigm may be shaped differently depending on context, namely developed and developing countries.

INTRODUCTION

The Agricultural Revolution between the 17th to late 19th centuries brought about productivity through the mechanization of farm work. As the human population continues to grow, however, the demand for land, food, and resources have become more intense making it necessary to reinvent the agricultural sector. Even with the continuous advancements in agriculture, the sector is still faced with several issues such as climate change, competition for land and water resources, food waste attributed to post-harvest handling and storage, and more. The 2018 Global Report on Food Crisis stated that “*out of the 51 countries that experienced food crises in 2017, conflict and insecurity were the major drivers of food insecurity in 18*

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countries, where almost 74 million people faced Crisis (IPC/CH Phase 3), Emergency (IPC/CH Phase 4) or Catastrophe/Famine (IPC/CH Phase 5) conditions” (Food Security Information Network, 2018). The United Nations (UN) Food and Agriculture Organization (FAO) estimates that farmers will need to produce about 70% more food by 2050. How is the sector prepared for increased production of food despite competing with humans for land? What is the optimal use for resources despite climate change? Will agriculture meet global food needs as projected by the UN?

In this regard, an emerging trend is the use of “*smart*” technologies in farming commonly referred to as Smart Agriculture. As CEMA (2017) puts it, the main difference between Precision Agriculture and its successor, Smart Agriculture, is that while the former improves the accuracy of operations and allows the management of in-field (or in-herd) variations by providing for plants (or animals) the optimal resources needed for growth, the latter uses big data analytics and artificial intelligence (AI) to act on data collected by the farm equipment. It has been suggested that Smart Agriculture solves the problem of generalization whilst providing autonomy for farm decisions enhanced by context, situation and location awareness (Wolfert et al., 2014). In this paper, we define Smart Agriculture as the use of precision agriculture technologies aided by big data and AI to make informed autonomous farm decisions that save resources in short term and increase the quality of produce in long term.

In essence, as has been done by blockchain and cryptocurrency in the payment industry, virtual reality in the entertainment industry, and trendsetters like 3D printing and augmented reality, big data and artificial intelligence (AI) in agriculture are disruptive technologies that, as defined by Christensen (1997), are changing the entire outlook of the industry through new ideas for problem solving with the hope of eventually displacing existing practices. However, as with any disruptive innovation, the impact on the target sector and society at large can have far-reaching implications. Big data and AI are already starting to reshape the manner we handle agricultural tasks such as harvesting, crop and soil management, and accounting for environmental impact on yield using predictive analytics. Examples range from robots employing advanced machine vision for harvesting pepper (Simon, 2018), to optimizing crop yields in India (Microsoft, Inc., 2018). Further, the socio-technical, and socio-economic drivers and challenges for the development and diffusion of smart agriculture are context dependent. While developed countries may be driven by a severe shortage of labor, developing countries are driven by the sheer need to support their fast-growing populations. The development and diffusion in developing countries will have to consider factors such as the nascent supporting technology infrastructure.

Being a novelty field with so much potential and rising popularity, several researchers have tried to measure the impact of Smart Agriculture and its effect on traditional agricultural practices. Big data management and analysis especially has been a major theme for most researchers in trying to understand the opportunities inherent in its incorporation into farms (Chi et al., 2016; Coble et al., 2018; Kamilaris & Prenafeta-Boldú, 2018; Nandyala & Kim, 2016; Waga & Rabah, 2014; Woodard, 2016). Wolfert et al., (2017) went further to develop a conceptual framework to analyze big data in Smart Farming applications from a socio-economic perspective. Other reviews have been more geo-specific: as has been done to understand applications of big data in developing countries (Ali et al., 2016; Misaki et al., 2018; Olaniyi et al., 2018; Protopop & Shanoyan, 2016); or more domain-specific: such as deep learning applications (Kamilaris & Prenafeta-Boldú, 2018; Zhu et al., 2018), hyper-spectral analysis (Khan et al., 2018; Thenkabail et al., 2012), and wireless technology (Mark et al., 2016). This chapter aims to contribute to existing literature by emphasizing the AI dimension of the conversation through an examination of how the relationship between these two innovations are disrupting agriculture. Specifically, this chapter addresses the following research questions:

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