The Future of Digital Agriculture: Technologies and Opportunities

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***Abstract*—This article presents key technological advances in the digital agriculture, which will have significant impact. Artificial intelligence-based techniques, together with big data analytics, address the challenges of agricultural production in terms of productivity and sustainability. Emerging new applications will transform agriculture from the traditional farm practices to a highly automated and data intensive industry.**

The digital revolution is transforming agriculture by using modern machinery, computerized tools, and information and communication technologies (ICTs) to improve decision making and productivity. The spread of several cutting-edge technologies, from GPS and remote sensing to big data, artificial intelligence and machine learning, robotics, and the Internet of Things (IoT), to agriculture is leading to increased yields, lower costs, and reduced environmental impact. Data-driven solutions are unlocking production potential in a sustainable and resource-efficient way.

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Precision agriculture management systems are allowing growers to benefit from this new tsunami of data they can gather. These systems collect, classify, and analyze vast amounts of data to detect patterns and solutions. They enable farmers to observe, comprehend, and manage the variability in their production systems by tailoring inputs to get desired outputs. GPS-controlled tractors can work around the clock, ploughing, planting, and harvesting while gathering continuous "on-the-go" georeferenced data. These self-driving vehicles can perform precise operations, with the help of GPS, Geographical Information Systems (GIS), and Variable-Rate Technology (VRT).

Weather stations supply a variety of agriculture-specific weather data. Such weather data are fed into the big data pool and promote farming decisions, such as irrigation decision making based on plant-water demand and accurate forecast of harvest dates. Remote and proximal sensing is used to capture invaluable soil and crop related data through hyperspectral, multispectral, and thermal sensors or cameras. Unmanned aerial vehicles (UAV) for agricultural purposes have the potential to be used from analysis applications, by producing soil and field three-dimensional models, data acquisition, and crop growth monitoring, to spraying or planting applications.[1] They are delivering regularly updated high-quality data to provide insight into crop development and highlight ineffective practices to track changes in health and maturity and to identify parts of a field experiencing "hydric stress." UAVs have also proven well suited for crop spraying, as they can apply fertiliser, herbicide, and pesticide liquids faster, more accurately, and with higher efficiency. Finally, UAV-planting systems are under development by using compressed air to fire seedpods directly into the ground.

The digitalization enables farmers to control their farms remotely and manage agricultural activities in a more effective way. In the near future, IoT will allow for automatic real-time interaction, controlling, and decision-making as agriculture sensors, actuators, and devices, as aforementioned, will all be interconnected. This will minimize human effort while saving time and increasing both yield and profit.[2] The emergence of cloud-based farm management platforms, such as the SmartFarm and Agrivi, aims to integrate these data coming multiple sources and include decision support systems. All these give growers insights for dynamic management planning, which have traditionally only been available to corporate megafarms. A general overview of the digital agriculture can be seen in Figure 1.

REMOTE SENSING

A variety of remote sensing technologies, from proximal sensors (within 1 m distance from the monitoring object), to drones, to satellites are used by the agricultural sector, providing insight to tackle the uncertainties coming from the variations of weather conditions and management strategies. These sensors exploit vegetation's reflectance properties and provide the opportunity to assess biomass, yield, acreage, vegetation vigor, drought stress, and phenological development, enabling early and efficient decision making in fertilization, irrigation, and pest management. Currently, the commercial availability of very high-resolution satellite data that varies in technique (active/passive, radiometer/scatterometer), spatial resolution (from submeter to kilometers), spectral range, and viewing geometry has opened up a number of new perspectives on the use of earth observation products in agricultural monitoring,[3] both at large and small scale areas. Similar information can also be retrieved by UAV remote sensing systems, which are often operated at very low altitude. Such systems use multispectral, hyperspectral, and thermal cameras that can measure heat, radiation, or light to capture a diverse electromagnetic spectrum. Although data retrieval in this case is less dependent on weather conditions, simplifying or even omitting atmospheric correction, these images cover much less area compared to the satellite products.

Technological advancements, such as analytical platforms, multispectral and hyperspectral sensors, as well as satellite data hubs that provide free and open access to satellite products [e.g., Copernicus Open Access Hub (ESA), EarthExplorer (United States Geological Survey), National Oceanic and Atmospheric Administration (United States Department of Commerce)], can act as the stepping stone for building reliable agronomic models on the basis of existing data generated by innovative monitoring applications. Furthermore, the development of agricultural infrastructure networks that allow faster and complete mining of the agricultural information through satellite data in deeper and broader horizons is necessary to improve the quality and efficiency of agricultural monitoring. This can also accelerate the delivery of agricultural data platforms, which could provide timely comprehensive information, to guide agronomic and economic decision making. However, the limited access of the farmers to the ground truth information becomes an obstacle to evaluate the crop status under various environmental

Figure 1. View of a digital agricultural field that has IoT devices to sense soil moisture, robotic vehicles (ground and aerial), and antennas to receive satellite images. Copyright: Authors; published with permission.

conditions. Therefore, efforts to establish networks of validation sites with the support of space agencies and/or environmental institutions are required.

Some of the challenges in agricultural remote sensing are related to standartalization of the data coming from different types of sources and different georeferenced systems, which cause problems on image projection and mapping. A space, aerial, and ground integrated structure to manage multiple sources of the remotely sensed crop parameters for agricultural data acquisition can also be the key to accurate visualization and monitoring of the crop status from multiple perspectives. The heterogeneity of satellite products in terms of spatial, spectral, temporal, and radiometric characteristics can also cause accuracy problems and be highly inadequate with the wrong approach. Finally, advanced remote sensing technologies generate a massive amount data of high volume and complexity, increasing the challenges of data storage and computation power, leading to serious issues in data management. For potential users, the wide variety of products can be confusing, and the analysis of the derived data is sometimes still too complicated.

ROBOTIC SYSTEMS TO AUTOMATE MONOTONOUS FARM OPERATIONS

Robotic systems have found fertile ground in agriculture tasks, due to the progress of ICT technologies, mainly advanced sensing, actuation, and AI. The increasing demand for accurate field operations, while reducing the farming inputs and environmental impact, constitute robotic platforms as the alternative of conventional tractors and implements. Small sized, electrically driven platforms are employed for a wide range of tasks, such as light ploughing, spraying, fertilizing, and harvesting. Especially in greenhouse production, due to the controlled environment conditions and structured cultivation properties, there are already commercial solutions offering significant advantages mainly for fruit harvesting. Finally, robotics have found several applications in livestock production, with more prominent evidence such as autonomous milking robots, manure scraping, and feeding platforms, combined with individualized care and health monitoring using identification technologies like RFID.

Considering the technological edge that these platforms can offer to agriculture, there are important challenges that prevent robotics from reaching their full potential. The existing prototypes and commercial platforms are limited to task-specific operations, whereas the scalability to different crops or environments is questioned. Furthermore, there are many interoperability and standardization problems when it comes to agrorobotics, with the communication of platforms and safety issues posing considerable barriers. Expanding the capabilities of robots from the lab and greenhouse environment to the outdoor conditions is crucial, when it comes to sensing under harsh environments and operating under unpredicting conditions. Regardless of the technical barriers, there is considerable skepticism related to social, economical, and ethical challenges in agricultural robotics. Labor shift from repetitive tasks to high-skilled engineering jobs and the imbalanced adoption of agritechnologies by farmers is expected to create social implications. Advanced intelligence and decision-making capabilities of robots results in debates about moral aspects and, overall, who has the responsibility for these actions. Moreover, expensive technologies and the demand for resources and infrastructures to launch robotics in the field will challenge the effective adoption of robotics from the feasibility point of view.

Moving toward the era of intelligence systems, robotic platforms will be the cornerstone of agriculture operations. UAV platforms will manage several light weight tasks, such as spraying and health inspections, as well as supervising ground robot fleets operating in the field. In the future, robots will be able to collaborate with humans without compromising safety in tasks like harvesting. To this end, robot cognition is expected to reach supremacy levels, with the systems able to have full environment awareness and clear reasoning of the decisions taken, for example, how to treat rotten fruit during harvesting or interrupt spraying when humans are in close range.

AI IN DIGITAL AGRICULTURE

AI applications in agriculture are increasing. Deep learning constitutes the state-of-the-art method for image and language processing with promising results for addressing farming problems, such as weed detection, plant disease diagnosis, crop type classification, and pesticide recommendations. Techniques stemming from deep learning, such as transfer learning or capsule networks, will lead future decision making by taking into account several factors, such as environmental conditions, harvesting practices, financial needs, soil characteristics, or water availability.

Deep learning methods, specifically convolutional nets (CNNs), are gaining fast growth for the automation of crop classification and disease/weed identification. The main reason is that contrary to the conventional machine-learning techniques, CNN training allows automatic learning representations of data with multiple levels of abstraction. Although CNNs are very data demanding, a technique called transfer learning is used to overcome this requirement by reusing patterns learned by state-of-the-art CNNs in the related tasks. Additionally, CNNs have also shown promising results with other problems, such as yield prediction, by extracting patterns from satellite imagery.

In the future, other techniques are expected to emerge solve open problems in agriculture. Regarding to computer vision related problems, such as crop classification and disease/weed identification, new architectures, such as capsule networks, will address current CNN limitations.[4] Contrary to CNNs, capsules (grouped neurons) consider the spatial relationships between entities and learn these relationships via dynamic routing, utilizing a nonlinear function called squashing. In regard to the use of reinforcement learning instead of the supervised one, architectures, such as imagination-augmented agents, will also play an important role, extending intelligence through imagination by learning to interpret predictions from a learned environment model.[5]

On the other hand, the extraction of information from natural language documents containing policies and regulations could be addressed by a recurrent neural network (RNN). Specifically, a subtype of RNNs called long short-term memories have arisen in the past years as good at modeling varying length sequential data, achieving state-of-the-art results for many problems in natural language processing (NLP), such as machine translation, information extraction, and text classification. Similar to computer vision, the use of transfer learning by word embedding techniques based on ELMO and

BERT will help to avoid the expensive creation of the necessary language model for more advanced NLP tasks. Such systems have been used to extract expert knowledge for regulations on pesticide use or agricultural knowledge from existing research databases.

Finally, another technique will be relevant in the near future: generative adversarial networks (GANs). This type of network could address the problem of data scarcity within agricultural computer vision when transfer learning and traditional data augmentation are not enough. The main advantage of GANs is that they can create pictures with synthetic "real" crops instead of just rotating or adding noise to the existing ones. This synthetic data could be used to improve the generalization ability of a CNN that obtains poor results due to the constraints in the size of the original dataset and the limitations of the traditional techniques.

CONCLUSION

Digital agriculture is developing rapidly, driven by many technological advances in the area of remote sensing, artificial intelligence, and robotic systems. These systems enable farmers to produce comprehensive, accurate, and transparent crop and livestock products, both at the national and regional levels and to get increased yield and quality, minimizing the environmental impact. However, several challenges and limitations, such as accuracy, interoperability, data storage, computation power, and farmers reluctance to adoption, need to be addressed for effective use of these technologies and widespread digital transformation of agriculture.

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