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Artificial Intelligence in Agrisystem

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Abstract

Artificial intelligence (AI) is a technology of 21st century that is limited to research in various fields of science and is lately a part of our daily life due to its rapid development. It has also gained importance in agricultural field and is achieving more applications. AI is applied in agriculture through two computer intelligence technologies: machine learning (ML) and deep learning (DL). These enable computer to learn and adapt processing input data pattern without human intervention by detecting hidden featuresof the subject under consideration. Generally, ML includes traditional methodologies that perform knowledge based learning by acquisition over features manually defined, whilst DL is a class of ML methods based on neural networks which learn to extract high-level hierarchies of features automatically from raw input. Moreover, there are diverse applications of AI in agriculture viz., crop management and health, crop husbandry etc. The wide-ranging growth of AI is mainly due to the power of high-performance computational devices, smart low-budget sensors for data acquisition, low-cost storage, wide availability of high-speed Internet for near real-time accessibility and sharing solution, abundant labeled data, great open-source software and algorithms used for knowledge extraction. AI systems presently help farming managers in agriculture more smartly to detect opportunities for crop productivity enhancement and guidelines for correct actions based on economic policy data trends. Unmanned Aerial Vehicles (UAVs), data collection services, satellite images, services providing data for input materials, pests and diseases analysis. In the near future, AI based services are likely to become a platform for agronomy, soil testing, crop health management and others where farmers may request AI to analyze raw data collected by low-budget robots, drones or smart phones by considering their special circumstances, cost and risk factors so as to take immediate action for further research and execution in various agricultural fields including soil microbiology and health with respect to macronutrients and micronutrients including trace elements.

Keywords: AI, Plant health, agriculture, AI devices.

Introduction

Humankind has been involved in agriculture since long and adopted this noble profession of farming for their survival. Agriculture is the cornerstone of our society and has undergone various changes over the last many decades through commercial breeding and molecular based techniques. Over the ages this world has approached new Modern Agriculture through improved agricultural technology in both hard and soft aspects. The impacts of successful agricultural technology innovations on agricultural development has also impact on rural transformation. Dozens of well-established measurement methodologies are found to measure the agricultural technology innovation level and its impacts globally in different continents, regions, and countries by covering the past, present, and future periods.

AI into the field of microbiology presents a promising avenue for understanding of microbial systems and their complex behaviors. AI in microbiology also poses significant challenges viz., data quality, interpretability of AI models, and ethical considerations must be carefully addressed to ensure the responsible and effective deployment of AI tools in this domain. Thus researchers, practitioners, and policymakers need to collaborate closely, fostering interdisciplinary dialog and sharing best practices. By doing so, we can harness the power of AI to unlock new insights into microbial biology, ultimately leading to improved diagnostics, therapeutics, and public health outcomes. AI technologies, coupled with deeper insights into microbial ecosystems will have impactful understanding of the microbial world.

AI Applications in agriculture

Before deploying AI in the agro sector, an in-depth understanding of the agricultural domain is of utmost importance. The largest portion of the knowledge is made by domain experts through various forms of data-like at the machines occasionally being gathered. In agriculture, the crucial need for interpretability requires machine learning models that could not be trained by the available data. It is of utmost importance to allow domain experts to interactively explore the decision logic of the model and thus improve the explanations by annotations of training data. AI is a major technology of the 21st century that is applied in almost every sector to make assessments and precise decisions based on the underlying conditions. AI provides computational intelligence such that machines can learn, understand, act, and respond to the varying situations based on the acquired knowledge. It is known as intelligence exhibited by the machines that allow them to perform tasks which normally require human intelligence.

AI is involved in many precision farming applications as it empowers farmers to act in a timely manner, improving crop quality and yield while reducing their cost to create sustainability in agriculture. AI sensors and UAV swarm systems are an essential part of precision agriculture. In precision farming, data captured from IoT sensors are used to predict the crop yield and weather prediction using machine learning (ML) which helps to meet the food production demand for agricultural land. ML is a subfield of AI in which programming is done to create algorithms that can automatically improve the performance of the computer through experience. It mimics the problem-solving ability of human beings and is hence considered as a decision-making tool in agri-farming system.

AI data Collection Technique

The development of artificial intelligence (AI) has given rise to various data collection techniques. These technologies have made a significant impact on the agricultural industry in recent years. The Internet of Things (IoT) is a well-known technology that facilitates the collection of data on various environmental factors such as humidity, temperature, soil moisture, wind speed, and rainfall, thereby establishing an event-driven technology. Cloud computing acts as an infrastructure for data storage, management, and monitoring. More importantly, data collection requires the integration of new technologies to be controlled more effectively. For an instance, unmanned aerial vehicles, which usually carry cameras to take pictures in the RGB (Red, Green, Blue), multispectral, or hyperspectral range, provide great insights into crop growth evaluation and environmental monitoring by its colour components. In recent years, a rapid advancement in sensor miniaturization has led to an increasing tendency to deploy them for agri-food systems. Optical sensors can provide data on land cover types, or the fluctuated time series. Electromagnetic spectrum can also assist in solving the problem of land cover composition estimation. Since there is an increasing amount of available data and a larger number of potential application domains, it is of great significance to find the appropriate computational intelligence methods for such dataof agrosystem.

AI based Yield Prediction Models in agrisystem

Accurate yield prediction is important for farmers, governmental authorities, agronomists, market analysts, and investors for economic gains. Understanding and predicting the yield of a crop are of great challenges due to interacting factors such as weather conditions, irrigation patterns, and soil conditions. Yield prediction systems have been widely used to provide valuable insights into farmers about the potential productivity of crops. In addition to supporting the prosperity of farmers, these tools also serve in major social needs such as food security and efficient resource usage. However, crop yield models are diverse and include all factors influencing crop growth leading to complex models that are difficult to interpret.

AI in Pest and Disease Management

The incorporation of automatic pest and disease risk detection systems in the world of agriculture through Artificial Intelligence in the Internet of Things (AIoT) technology, facilitates monitoring of crop conditions and consequently pest and disease risks. Based on off-the-shelf sensors, adapting those to extreme conditions, low-cost and low-power sensor nodes are developed. With the use of low-cost sensor nodes and cloud services, it is possible to apply AIoT technology in agriculture. Given the deployment in the field of IoT sensor nodes, an initial detection method based on a decision tree algorithm was proposed, emphasizing the idea of accessibility and low cost. Adapting to the absence of data in crops, the capture of information required for model training is feasible due to the virtualization of the application, and with the help of agricultural experts, synthetic data pools which enable the teaching of models for different agricultural crops. Results and the simplicity of the model can be deployed in lower computational and economic resources. Signal processing techniques can be included in the application improvement to refine model detection. The model re-training given the emergence of new pests and diseases is linked to the update of alert conditions relative to each crop and other types of crops used. These are highly relevant points from an AIoT system perspective, since having a sensor nodes network in the crop which facilitates a more precise detection of the location where the risk has emerged and also possible to study the occurrence and recurrence of pests and diseases in the crop over a period of time.

Machine Learning for Pest Detection

The skill of machine learning allows PCs to obtain or acquire knowledge from data and then utilized in improving the performance of pest and disease detection methods. Initially, pests and diseases are detected by using machine learning models by extracting the signs, images, and videos reflecting the characteristics of incursions from visual sensors implemented in calibration systems. For making correct detection, the decline of recognition accuracy occurs when illumination variation occurs coping with 3D rotation, occlusion, motion, and further analysis. Object observation is majorly divided into two categories including tracking and detection based on previous object information.

Automated Farming Equipment

Modern inputs such as irrigation, fertilizers, and pesticides have engendered an explosion in agricultural productivity but with marked consequences for the overall human ecological footprint will continue to grow thus bringing both promise and peril. Uncrewed vehicles called drones and robots are automated sensing platforms which are capable of more kinds of measurements than performed at the ground level.

Drones in Agriculture

To categorize drones, massive and small UAV systems coexist. The latter can be positioned in three classes: category 1 under 5 kg; category 2 between 5 kg and 25 kg; and category 3 over 25 kg. These smaller UAVs can be either multi-rotor, resembling mini-size helicopters, or fixed-wing, resembling mini-size planes. Multispectral and hyper-spectral sensors can be used for optical imaging and are becoming more affordable and lighter. They can be mounted on board both professional aircraft and drones. Synchronized RGB and multi-hyper-spectral imaging systems is possible. They relay information on crop health and vigor and the UAVs fly previously-defined routes, fix and variable wings movements can be synced with the sensors captures commands. For yield mapping, the UAV can be mounted with professional fixed-wing aircraft, global navigation satellite system (GNSS) and differential global navigation system (DGNSS) receivers providing centimeter-level location accuracy. The drones-driven equipment, products, and services will be eventually termed drone agriculture, unmanned aerial vehicle agriculture, or aerial robotics in agriculture. The organizations processing of UAV data and providing drone services to farmers' co-operatives and companies are visible in maps. These organizations offer processing services to farmers alongside agriculture.

Robotics for Planting and Harvesting in Agri-system

In autonomous tractor design similar work may be found. Robots and other farming type machines with speed and position control problems in agricultural processes may be benefitted with this type of design. However, this design was only tested on a small farmer tractor and working model. Tests on big sized tractors have not yet been tried. This initial model can be used on semi-dynamic applications like agricultural robots in non-aggressive tasks. Combining this design with dynamic or more aggressive applications needs improvement in the mechanical structure like adding more speed feedback sensors and a better controller design.

Soil Quality Assessment Tools through AI system

Agricultural productivity entails the customer-centric output of crops produced on quality soil. On the other hand, soil quality entails the capacity of soils to function within ecosystem and land-use boundaries that are natural for soils of similar origin. Thus, there exists a soil quality versus agricultural production dilemma; soils being mined for their quality while they need natural fertilizers. Digital soil quality assessment entails stepwise formulation of a soil quality index and soil property mapping through AI system.

Output Supply Chain Optimization with AI

The first area of impact involves combining smart data and chatbots to allow sourcing buyers to delegate supplier communication and order processing to virtual assistants. AI applications that automate and facilitate RFQ bid preparation and evaluation thus provide access to the supply market at an attractive cost and allow for higher quality bids. AI also allows buyers to analyze suppliers and markets in real time to make turns and adjust strategies. Procurement chatbots will provide a more streamlined entry to, and oversight of procurement systems. In addition, many companies are examining the use of AI applications to mine data from unstructured text formats such as emails, letting these applications while working with the company and HR issues. Net contribution is the difference between the total profit obtained by selling the product and total costs incurred across the entire supply chain.

Predictive Analytics and Demand Forecasting

As with many sectors, strategists and decision makers in the agricultural sector have a requirement to predict key measures such as product and feed pricing. An added complication is that whereas, in many other industries, modifications or improvements to a market pricing model can be tested and simulated, inputs to models of the Agri pricing are wide-ranging hypotheses thus needed for further demand forecasting. Predictive algorithms in Agri Analytics have shown to be very difficult due to the wide range of parameters and often unpredictable nature of some of these variables while working through AI in agrisystem.

Sustainability and Environmental Impact on Agrisystem

Agriculture is one of the greatest challenges of the twenty-first century. The increase in the global population is a point to be considered; the population is expected to reach 9.7 billion by 2050. To feed this growing population, food production must increase by 70% as compared to 2006. However, food production comes much more often at the cost of environmental degradation. Studies speak of the dominant role of agriculture which plays importance to humans directly by impacting biodiversity as agriculture being the primary contributor to biodiversity loss on our planet. To mitigate this degradation of environmental quality while keeping up ready to meet the demands of a growing population, sustainability is needed in the food system at all levels. Sustainability can be represented through economic profit, social equity, and environmental quality. In that direction, AI is expected to positively influence economic and social sustainability in ameliorating the agri-food system. For the economic perspective, as in many other domains, AI is considered to be one of the technologies with the greatest potential for improving profit-making. AI will support farmers in sourcing important input data, making better predictions, and analyzing the predicted yield of resilient crop cultivars. Studying the environmental performance of current farming operations will support a move toward better-invested resource usage; for example, improved predictions of when and what input to apply that best can drastically enhance nutrient usage, thus reducing the loss of fertilizer. To do so, questions of model interpretability arise; furthermore, farmers may need to rely on new sensor and software services providers of AI in different agrisystem. AI also has a positive impact on the social perspective of sustainability; the agri-food domain which is often considered as a domain with low job satisfaction.

The application of AI in agriculture would be a substantial improvement regarding the quality of the work for all sectors in the food system. It will lead to a higher blurriness of work and work hours and therefore more flexibility for the workers. AI is expected to work more production-intensive measure which would lead to value-added processors and ecosystem services providers in agrisystem.

Reducing Carbon Footprint through AI

Applying machine learning and predictive models is one way for the research community to help agriculture in fighting for climate change. Cleverly designed low-cost sensor networks and remote sensing systems can provide continuous monitoring of farmland health, climate impacts and water availability. Data can then be processed with artificial intelligence (AI), statistical analyses or models to identify imminent agronomy actions. Once a basis for control and preventive intervention is established, the evaluation of technologies and methods for the continuous monitoring of greener impacts can take place for economic gains in agrisystem.

Biodiversity and AI Applications

Remote sensing, inexpensive sensors, and UAVs empower farmers and field agents to adopt practice-level and field-level precision agriculture practices. The efficient and widespread adoption of advancements in crop genetics and genomics into plant breeding is crucial for ensuring global food security in the face of fluctuating climate conditions. Seed demand forecasting is vital for ensuring timely availability and quality of crops seed. Estimation of dynamic demand and supply at different levels is thus essential for rational planning of production and distribution schedules. There are multitudes of crops sown in diverse climatic and soil conditions across the globe. Crop yield forecasting measures the rate of grain production of crops in a given area. Accurate crop yield estimates are essential for informed market interventions and food security. The integration of massive, multi-source, and heterogeneous data can provide insights into large-scale yield estimation. Addressing data implementation issues and challenges is vital to build a global yield estimation system through AI in agrisystem.

Challenges and Limitations of AI in Agriculture

AI models for agrifood systems should consider not only the wide variety of agrifood products produced in different regions but also the fact that the growth cycle of crops is generally long which limits the real-time performance of technologies in certain applications. Seasonal characteristics exist in agriculture activities as some crops can only be grown in summer while others are cultivated mostly during cold seasons. This leads to seasonal production of certain agrifood products and results in long periods without production in each cycle. Thus, AI models for agrifood systems must consider these aspects regarding seasonality to prevent information leakage. Relying solely on a single data resource may not lead to effective judgments. In the agrifood system, data are heterogeneous as it is obtained with different modalities from various sources. For instance, data obtained from weather sensors and aerial images detected by drones are helpful to estimate raw material harvest of various crops. However, sound signals of machines and videos collected by moving smart tractors provide insights for machine operations. The improvements in such technologies generate large multimodal data with different structures at different time intervals. Attaining high efficiency in the acquisition, integration, and collaboration of multimodal data have emerged as a major challenge in production-related applications in agriculture.

AI Technology Accessibility Issues in Agrisystem

AI-powered innovations have a powerful potential to improve agriculture, bringing new models for production, distribution and consumption. However, simply creating a technological solution does not guarantee its effective application. Developers must be aware of the natural monopolies that are being created over the data, the seeds and the pesticides that are used to train machine learning models under

AI technology system.

Future Directions for AI in Agricultural Research

Agriculture will require significant research into areas that drive advancements with artificial intelligence (AI) specific to various crops+in cereals, horticultural and forest plants. It is critical to establish a robust data collection and curation ecosystem on which researchers and manufacturers can create innovative predictive analytics systems and drive advancements in automation of technology solutions, such as robots and drones in pesticides selection and application as well as soil analysis with respect to macro and micronutrients including trace elements. Big data pipelines, capable of ingesting terabytes of data every day, would need to be established in partnership with agriculture researchers and companies focused on data collection and analysis. Specifically, focus would be aimed at aspects of data that can assist in predicting crop yield, disease diagnosis and infestations as well as stress tolerance. Collaborative efforts involving researchers, manufacturers and farmers will be crucial to the development of an effective software-specific to agronomic practices and applications under different set of environment conditions. Such research has the potential to have positive global impacts, including reducing environmental damage and enhancing agricultural production for economic gains.

Emerging Technologies

The data involved in the applications of AI techniques are organized which facilitates the understanding of various advance. The rapid development of AI techniques provides efficient ways to handle, preprocess, and analyze the data in the agrifood sector. Both traditional ML (Machine Learning) methods and advanced DL (Deep Learning) technologies are heavily adopted by practitioners and researchers in various fields of agriculture, husbandry, aquaculture etc. The rapid adoption and dissemination of AI in agriculture have its promise to boost productivity and sustainability by production-oriented processes and action-related precision alternatives which will have impact on regulatory intervention and will help policy makers in future endeavors.

Ethical Considerations of AI in Agricultural system

AI systems in agriculture are at risk of biases that could mean that the technology would disfavor some parts of the farming community, particularly among growing companies as opposed to those who have just established. These biases could be introduced by the data used to train the algorithm. In most deep learning algorithms, these training datasets are biased due to the collection systems. Hence, a greater effort should be expended to improve the dataset so as to build a fairer and fast agri- AI algorithm. This is a complex situation since even a perfectly fair algorithm can still produce disparate impact.

Impact of AI on Employment

AI reduces employment and while providing new measures of the AI impact in a few countries, and estimating their relationship with employment, the estimates do not try to find out why the impact of AI differs across countries, such as the role of labor costs or protection, the type of government, or the education level of the workforce. In addition, it is likely that the circumstances in some countries are harder to ascertain than others. Active research streams focus on developing AI-based solutions that adopt one or more types of models to address agrifood systems problems. The application of AI methods

in agriculture, with increasing attention on multi-site farm-level data, multi-scalar methods, and coordinated management across multiple systems need to be addressed.
AI into the field of microbiology presents a promising avenue for understanding of microbial systems and their complex behaviors. AI in microbiology also poses significant challenges viz., data quality, interpretability of AI models, and ethical considerations must be carefully addressed to ensure the responsible and effective deployment of AI tools in this domain. Thus researchers, practitioners, and policymakers need to collaborate closely, fostering interdisciplinary dialog and sharing best practices. By doing so, we can harness the power of AI to unlock new insights into microbial biology, ultimately leading to improved diagnostics, therapeutics, and public health outcomes. AI technologies, coupled with deeper insights into microbial ecosystems will have impactful understanding of the microbial world.

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