Challenges Facing Artificial Intelligence Adoption during COVID-19 Pandemic

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Contributor: Debesh Mishra, Kamalakanta Muduli, Rakesh Raut, Balkrishna Eknath Narkhede, Himanshu Shee, Sujoy Kumar Jana

The coronavirus (COVID-19) pandemic has witnessed a significant loss for farming in India due to restrictions on movement, limited social interactions and labor shortage. In this scenario, Artificial Intelligence (AI) could act as a catalyst for helping the farmers to continue with their farming.

Keywords: agriculture ; agri-food supply chain ; farmers ; Artificial Intelligence

1. Introduction

The practice of farming involves not only a number of options but also dealing with a number of unknowns. Managing the unknowns/uncertainties with farming is essential, but it can be difficult under the circumstances of shifting climates, seasonal variation of temperatures, varying costs of farming materials, unviable crops, soil degradation, crop damage caused by pests, crop suffocation caused by weeds, and so on. On the other hand, technological development has pushed various applications to the boundaries helping toward the goal of combining a natural brain with an artificial one. This has resulted in the emergence of a new field of application using “Artificial Intelligence (AI)”, which refers to an intelligent machine/computer that can be made to think the way human thinks. The use of AI is becoming more common in the agricultural sector with the intention of developing innovative strategies for the continuation and enhancement of agriculture. The application of AI in agricultural sector is although evolving, it will likely be a reality with the development of other related technologies such as “big data analytics, internet-of-things, sensors and cameras, robotics, and drone technology”, etc.

AI assists in providing predictive insights for agricultural activities such as “plantation- and harvesting-information” by analyzing soil management data sources [1]. These data sources include temperature, weather, soil and moisture analysis, and crop performance histories. As a result, crop yields can be increased while simultaneously reducing the amount of water, fertilizer, and pesticides used. Because of the increased use of AI technologies in agriculture, there is a potential for significant reduction in the negative impacts on natural ecosystems and on the safety of agricultural workers. This will further contribute to the maintenance of decreased food prices and increased food production thereby meeting the growing global population need. There has been interest in the field of AI [1][2][3] for decades and has been envisioned as a smart-machine supremacy that would take control of the planet and carry out the mundane, everyday tasks [4]. Because of its enormous benefits and improved performance, AI has emerged as a critical agenda of many companies’ business models [5]. This is due to the fact that AI has evolved into a strategic system that can be applied across all industries. In the recent past, there have been a number of conceptual and empirical studies, and in many cases, the application of AI by regional and international government bodies have been demonstrated from both the academic and practitioner perspectives [6]. In addition, a number of conceptual and empirical studies have been conducted. AI has opened up a wealth of opportunities in a variety of sectors, including healthcare, agriculture, industry, and the environment [7][8].

2. Agriculture and Artificial Intelligence (AI)

Agriculture is a sustainable foundation of the economy [9][10][11], and it plays a critical role in both long-term development of the economy and the structural transformation of societies [11][12][13][14][15][16]. Historically, the majority of agricultural activities were restricted to the growing of crops and the preparation of food [17]. On the other hand, during the past twenty years, the agricultural sector has become increasingly involved in the production, processing, and marketing of crop and livestock products, in addition to their distribution. These activities are within the agri-food supply chain. At the moment, it functions as a primary source of income and, thereby, contributes increasingly to GDP [18]. This means that it not only functions as a source of national trade but also helps in reduction of unemployment, the provision of raw materials for other industrial activities, and the overall growth of the economy of the country [19][20][21]. In order to satisfy the increasing food demand, agricultural and food production will need to increase by 70% by the year 2050 [22], the year the global population is estimated to surpass 9 billion. However, it is difficult to meet this target in the face of a range of challenges like resource shortages, climate changes [23], the COVID-19 pandemic, and extremely pessimistic socioeconomic projections. As a consequence, maintaining the viability of the agricultural sector is essential for ensuring food security in addition to eliminating hunger for the world's expanding population. In addition, a well-documented management solution has become a prerequisite for quality conformance in the food chain due to the emergence of food-safety issues, such as "spongiform- encephalopathy of bovines and dioxins" in poultry [24].

A systematic transition from the existing paradigm of increased production to sustainable practices in agricultural sectors is an immediate need. This can assist farmers and consumers in making more informed-choices by implementing sustainable practices to effective solutions, particularly when utilizing digital-technologies such as "Internet of Things (IoT)"; "Machine Learning (ML)"; AI; and so on. Soil management is an essential component of agriculture. An in-depth understanding of the myriad of soil types and conditions is essential for maximising crop production while simultaneously protecting the earth's natural resources. The effects of soil-borne pathogens can be controlled through proper management of the soil [25]. For example, the AI-based soil-management technique is known as "management-oriented modelling", which consists of a set of possible management options to assist in minimising nitrate-leaching. This was done to protect the environment. It included a simulator for the purpose of evaluating each alternative and an evaluator to determine the user-weighted multiple-criteria alternative [26]. Also a remote sensing device incorporated into a "higher-order neural-network" was appropriate for the characterization and assessment of the soil-moisture dynamics [27]. While the existing "coarse-resolution soil-maps" are combined with hydrographic parameters derived from a "digital elevation model", a model known as "artificial neural network (ANN)" helps predict soil-textures based on their characteristics [28].

Crop management begins with sowing and growth monitoring, followed by harvesting, storage, and distribution of crops. An agricultural management system such as "precision crop management (PCM)" is designed to focus on crops and soil-inputs in accordance with field requirements for the optimization of profitability and protection of the environment. The lack of timely as well as distributed-information on crops and soil-conditions has been reported of hampering PCM [29]. Farmers need to combine various crop management strategies to be able to deal with water shortages brought in by soils or limited irrigation [30]. This is necessary for farmers to be successful in farming. For the evaluation of the operational behaviour of a farm system and the estimation of crop production, gross-revenues, and net profits for both individual fields and the whole farm, PROLOG has been found to be effective in utilising weather data, capacities of machinery, availability of labour, and information on prioritised and permissible implements, tractors, and operators [31]. Weed is responsible for a steady decline in the anticipated yields and profits made by farmers [32]. An uncontrolled weed infestation results in a 50% yield reduction for corn crops and dried beans [32], and about a 48% loss in wheat yield [33][34]. A "global positioning-system (GPS)" controlled patch-spraying based on an AI approach can be used for weed control in agriculture [35]. A drone travelling at a speed of 1.2 km-per-h has been successfully used in weed control [36]. In most cases, the crops are laid out in rows; consequently, the application of a crop row-detection algorithm helps in properly separating the weeds and crop pixels [37]. This is something that can be utilised by an "unmanned aerial-vehicle (UAVs)" for the purpose of performing efficient weed control. In addition to this, there is a demand for the implementation of AI strategies in disease management and control [38][39][40].

3. AI Applications for Agriculture and Food Sectors Improvement

AI is a creative tool that models how human intelligence and aptitude are processed by machines, primarily by computers, robots, and digital technology [41]. The application of machine language (ML), which fosters both inventiveness and productivity, is one of the primary focuses of AI. The development of AI has paved the way for applications of the technology in the agricultural and food industries. Farmers are turning to AI tools in the hopes of discovering more efficient methods to protect their crops from being destroyed by weeds. The application of innovative AI-based techniques to the agri-food supply chain has a number of benefits, including a reduction in the cost of training, a reduction in the amount of time needed to solve problems, a reduction in the number of errors made by humans, a reduction in the amount of human intervention that is required, and intelligent decisions that are affordable, accurate, and satisfactory [42]. The application of ML algorithms to the various nodes that make up the agricultural supply chain is becoming increasingly important [43]. Numerous studies examine the significance of agricultural crop yields as a means of enhancing plant management. As a result, ML and AI algorithms can help consumers and farmers make optimal decisions for crop yield forecasting. This can lead to higher yields and greater profits for everyone involved. In recent years, various ML algorithms, such as ANN, regression, Bayesian networks, decision trees, deep learning, and others, have been utilized for the purpose of developing prediction models [44][45]. According to the findings of Arvind et al. [37], it is possible to effectively predict and manage drought by combining the use of an ML algorithm with the utilization of other sensors and systems, such as "Zigbee and Microcontroller". Further, the ANN feed-forward and ANN feed-back propagation techniques were applied in a smart farm in order to make the most of the available water resources [46]. Few examples of technology that is based on AI include UAVs and robotics, block chains [47], geographic information systems [48], and satellite navigation. Agricultural drones can now provide farmers with water, fertilizer, and pesticides, as well as filming, photographing, and creating maps of plants and fields in real time [49]. This functionality of agricultural drones could better assist farmers in making management decisions.

Adopting sustainable farming practices has been encouraged in order to safeguard natural resources and accomplish the "sustainable development goals (SDG)". Utilizing digital technologies in agriculture, notably AI, machine learning, deep learning, and the technology behind block chains, could result in potential gains. The growth of technology has resulted in an increased demand for AI, which can perform difficult jobs more quickly and efficiently, as well as at a reduced cost [50][51][52][53][54][55]. In the midst of the COVID-19 pandemic, the use of cutting-edge technology based on AI may prove to be a superior answer [56]. Moreover, AI has been used widely in the fight against the COVID-19 pandemic [57][58][59][60][61][62][63][64][65][66][67][68][69]. In addition, the technologies of "Industry 4.0", which take the real-time information provided by AI and IoT. Printing the necessary medical components is possible by combining cutting-edge design software with digital manufacturing technologies such as 3D printing [68][69]. According to Panpatte [70], AI enables the collection of a greater quantity of data from public websites as well as from the government, which it then analyzes and uses to give farmers solutions for a wide variety of perplexing problems [71]. In addition to this, AI has begun to play a large role in people's day-to-day lives, with the intention of modifying the environment through the extension of people's perceptions and capabilities [72][73][74][75].

4. AI Implementation Challenges in Agri-Food Supply Chain during COVID-19

The challenges associated with the implementation of AI in agri-food supply chain in the global level as well as Indian context are discussed in the following sub-sections.

4.1. AI in the Global Level

More sustainable supply chains, particularly those connected to the food sectors, are required as a result of increased globalization amidst world's population growth [76]. Moreover, an intelligent system's major attribute is considered to beits' ability in executing required tasks in a very short-time with accuracy. The majority of systems fail in achieving the required accuracy or response-time or both. However, the selection of task strategy for users gets affected by system-delay and the selection of strategy is usually a cost-function-based hypothesis that combines the factors such as: the required efforts in synchronizing the input-system's availability and the afforded accuracy-levels. Normally, people looking for minimum efforts and maximum accuracy-levels tend to choose among three-strategies: "seamless-performance, quickness, and control" features [77]. The volume of input data influences the strength of an intelligent system. An immense volume of data is required to be monitored by a real-time AI system that needs to filter-out much of the incoming data. However, to significant or unexpected events, it should remain responsive [78]. In order to improve the speed and accuracy of systems, only very relevant-data should be used with an in-depth knowledge of the task of the system. For developing an agricultural intelligent system, combined efforts of agriculture specialists from various fields are required along with the cooperation of the farmers [79]. For agricultural management, the emerging expert or intelligent systems have been useful tools in providing integrated, area-specific, and interpreted guidance. However, as the development of these intelligent systems is fairly recent for agriculture, the use of these systems in commercial-agriculture is limited [79]. In a study, a discussion has been made on various application of thermal-imaging like "pre-harvest operations, field-nursery, yield-forecasting, irrigation-scheduling, termite-attack, green-house gases, and farm-machinery" [80]. Furthermore, a distributed wireless-network has been used for controlling irrigation-process from a remote-place [81].

4.2. AI in the Indian Context

The AI applications need to be more robust in agriculture for exploring its enormous benefits [82][83]. The outcome of cultivation largely depends on various cognitive-solutions' reception. While, a large scale research is still in progress and the industry has been under-served, some applications are still available in the market [84]. An automated irrigation-system using GPRS-module as communicating-device was developed and it was found to result in 90% more water-savings than conventional irrigation-systems [85]. Katariya et al. [86] have suggested the use of robot in the agricultural fields for spraying of pesticides, dropping of seeds, water-supply and ploughing activities. The working of the robot was designed to follow white-linetrack of the needy tasks, while other surfaces were regarded as black/brown. Kodali and Sahu [87] have discussed the use of “Losant platform” in order to monitor the agricultural land and also, for intimating the farmers via SMS/e-mail for any variances in the system. Roopaei et al. [88] have discussed the use of cloud-based thermal-imaging system for the irrigation in agricultural sector. Since AI uses big data, thus the looking-up method and training need to be properly defined to achieve speed and accuracy [89]. Although, the AI-based systems are gradually embedded in variety of products and services, ensuring successful working of human and AI together remains a challenge. A flexible subsystems is required that will interface with an integrated environment for AI-based robotics’ technology [90], and have more capabilities in accommodating a large amount of user data.

AI-based systems are unable to learn from their environment like human-being. However, the AI-based systems perform better with given parameters and rules. But the major limitations are with decision-making where context plays significant-role. The various cognitive solutions available for agriculture are very expensive, and thus the AI solutions need to be more viable to the farming-community [89]. A digital-agriculture refers to the use of “hi-tech computer-systems” for calculating a number of parameters like weed-detections, crop-predictions, yield-detections, and crop-quality by using the ML [91]. Bannerjee et al. [92] have offered a brief-overview of AI techniques by covering AI advancement in the agriculture domain from early 1980s to 2018. Jha et al. [93] have discussed different automation-practices like “wireless-communications, IoT, ML, AI, and deep-learning”. Further, they discussed about a proposed system’s implementation in botanical-farm for leaf and flower identification in addition to watering by using IoT. The growing demand towards the “AgTech industry” with the use of computer-vision and AI might be a path for sustainability in food-production for feeding the future [94]. Talaviya et al. [95] have discussed various methods used by drones in agriculture for spraying in addition to crop-monitoring.

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