ARTIFICIAL INTELLIGENCE (AI) AS SUSTAINABLE SOLUTION FOR THE AGRICULTURE SECTOR: FINDINGS FROM DEVELOPING ECONOMIES

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Abstract. *Agricultural production plays an important role both in national and global economies. The efficient and safe methods of sustainable agricultural production is crucial, and the use of information technology is imperative to meet this end. Among the available information technology tools, this study highlights the IT based cognitive solutions supported by the artificial intelligence (AI) algorithm for sustainable solutions in the agriculture sector of developing economies. For this purpose, a systematic review of 87 papers has been conducted in the chosen last 20 years from 2000 to 2019 to identify the major trends, challenges, limitations related to the applicability of AI-supported cognitive solutions in the agricultural industry of developing countries. The results derived from the extant literature represent some major flaws in the existing technological & cognitive solutions being used for agriculture means in the developing economies, with special emphasis on the lack of advanced AI techniques that are required for the development of robust and precise farming methods. This is due to the farmers' inability to use sustainable technological solutions that are limited by the high cost of available technological tools. Moreover, human expertise is scarce and very costly in the agriculture industry. Hence, there is a need to actively introduce the concept of AI in the agriculture sector by making AI more viable and affordable for the farming community in developing economies. Besides, there is also a need to create a centralized AI model for the agriculture industry which will integrate AI into a single central system for the entire economy that could be used in various enterprises of the agriculture industry*

Keywords: Agricultural Industry, Artificial Intelligence, Developing Countries Information Technology, Sustainable Agriculture

1. Introduction

Artificial intelligence represents the intelligence and reasoning ability of the technological system supported by supercomputers and sophisticated algorithms to fulfill the creative and innovative functions that are traditionally considered as the prerogative of human beings (Rassel & Norvig, 2006). The industrial revolution of the 19th century had been successful to deploy technology as a human labor substitute. Presently, human civilization is moving towards the 6TH technological generation and, the application of artificial intelligence (AI) is considered the most important step towards the projected sustainable and technological advancements in the agriculture industry (Kablov, 2010; Kushkhova et al., 2019). It can potentially take over the traditional human role in the agriculture sector by positively affecting the global agricultural productivity, environmental factors, equality, and inclusion on both short and long terms (Vinuesa et al., 2018).

The United Nations reports that approximately 20 to 30 billion dollars were globally invested in research and development activities alone during 2016 to make advancements in the field of artificial intelligence (Shahzad, 2018). Parallelly, the agriculture sector is one of the most important growth drivers (Aganbegyan, 2017) in the developing economies due to its major share in the GDP, national employment, and investment. This implies that AI and emerging computer technologies can bring a paradigm shift in the agriculture and farming industry (Horvath et al., 2018).

Farmers supported by digital cognitive solutions can enhance agricultural surplus for the global economy. Furthermore, currently, there is a drastic change in the consumer preferences about the farming product as they are not only valuing the high-quality goods, but they also question the sustainability of agricultural practices (Miranda-de la Lama et al., 2019). For instance, most of the consumers emphasize to observe the element of animal welfare while producing agricultural products. They also demand proper scrutiny of the supply chain to incorporate a sustainable approach in the supply chains of the agriculture industry (Mangla et al., 2018). The myriad of AI & digital technology can help to address the socio-economic concerns and sustainable farming needs of the 21st-century. Therefore, the agriculture sector in developing economies requires swift incorporation of artificial intelligence to modernize the farming mechanism and boost the process of economic development (Dharmaraj & Vijayanand, 2018).

2. Literature Review

The literature review is based on the systemic review of 87 research papers for the selected period from 2000 to 2019 to explore the major challenges faced by the agriculture sector in the developing and global economies. Additionally, the prominent AI and cognitive solutions are also reviewed to propose comprehensive AI and digital solutions that are tailored to the unique needs of the agriculture industry in developing economies. The literature review highlights that currently there is an increasing trend of using AI technologies in agro-industry as the economies which prioritize the integration of AI in their agriculture sector and continuously make its application deeper and wider due to which they are reported to win in the international agriculture market (Kushkhova et al., 2019). The growth of the global agriculture sector depends on the strategic integration of technological instruments. The agriculture sector is witnessing substantial growth due to the application of digital cognitive solutions (Dharmaraj & Vijayanand, 2018). The widespread use of digital technology solutions can bring sustainable growth to the global agriculture sector. The use of technological equipment such as drones and other electro-mechanical devices has become the need of modern farming. Novel methods of farm processing can fulfill the increasing food demand on a global scale (Lievonen, 2000).

The literature on artificial intelligence & agriculture industry in the developed economies such as Great Britain, Denmark, Holland, Australia, Germany, etc. depicts that the adoption of emerging technologies and implementation of AI in the basic agricultural cycle results in increased volume of production without increasing the traditional (land) factors or production resources (Kaab et al., 2019). The modern agro-industry in developed countries has been translated into a highly competitive and globalized industry mainly due to the use of artificial intelligence and emerging computer technologies (Jha et al., 2019). The agricultural production was recorded to have increased by technological innovation as evident from the 1920-1995 pattern of agriculture productivity in the USA. Besides this, the share of human labor in the agriculture sector had reduced to 2.6 percent (3.3 million people) from 26 percent of people (9.5 million people) during this period of time. The United States Bureau of Census reports that nevertheless, the share of human labor had declined to 2.6 percent at the end of 1995, but the farming output was enhanced 3.3 times of that 1920 (Sunding & Zilberman, 2001).

Different cognitive innovations and sustainable solutions have effectively enhanced agriculture productivity in developed countries whereas, on other hand, the agriculture industry in developing economies encounters several socio-economic and technological problems due to the lack of advance cognitive solutions and emerging computer technologies. The main reason behind the poor performance of the agriculture sector in developing economies in the eyes of researchers is the poor and inadequate implementation of advanced technologies in the agricultural industry such as AI and other digital sustainable solutions (Aganbegyan, 2017).

The growing global population feeding, particularly in third world countries, requires a sustainable solution for food production, but the size of arable land is reducing in emerging countries (Dengel, 2013). Additionally, the expected and observable shifts in the world climate, changing patterns of rainfall, global warming, drought, and the increased frequency and duration of extreme weather conditions have combinedly deteriorated the traditional production areas (Gebreegziabher et al., 2020). It has brought additional risks and uncertainties for the global harvest yields that make the farmers more vulnerable in the underdeveloped economies. Besides, the complexity of these challenges is further compounded due to other short-term events that are difficult to predict such as financial crisis, epidemics, or price volatility for agricultural raw material and products (Burney & Naseem, 2018). To overcome this obstacle, the agro-industry in the emerging economies requires sustainable and continuous agricultural advancement in all modes of agricultural production. Hence, the agro-industry across the world and particularly in the developing countries require new technological solutions in the form of artificial intelligence to address all the issues related to the agriculture industry ranging from crop yield, complexity, uncertainty, and fuzziness inherent in this domain (Bannerjee et al., 2018).

Even though, after reviewing the existing literature on artificial intelligence and its implications for the global agriculture industry (Kushkhova et al., 2019) there remains a critical research question overlooked and unanswered, that is "what is the effect of AI on all aspects of agricultural productivity in the developing economies?". To the best of our knowledge, at present, there is no published research study assessing the extent to which artificial intelligence may influence all dimensions of agricultural productivity in developing countries including the major challenges and solutions to the agriculture sector. Thus, this research question encompasses a critical research gap and the current study takes the endeavor to investigate the potential challenges and applications of artificial intelligence in the agriculture industry from the prospect of an integrated system in which AI is capable of achieving enhanced agricultural productivity by overcoming the traditional challenges faced by the agriculture industry in the developing countries.

3. Key Challenges Faced by the Agriculture Sector in Developing Economies

Campos et al. (2018) report that each year there is an annual increase of 70 million people in the global population. This shows that there would be approximately 10 billion people in the world till the end of 21 century in case this upward shift persistently continues throughout the century. Additionally, the emerging economies comprise a large portion of the projected world population (Boserup, 2017). The increased world population has put a greater amount of pressure on the agriculture industry particularly in the emerging economies as there is a need to grow sufficient food for the growing global population that majorly resides in the developing countries (Elahi et al., 2019). Furthermore, the increase in the global population also generates residential spatial problems. Almost, 70 percent of the global arable land is converted into residential and commercial infrastructure (Abdullahi & Pradhan, 2018; Wright, 2006; Elahi et al., 2019). Hence, there is a range of technologies as well as socio-economic problems being faced by the global agriculture industry, in particular by developing economies. The foremost challenges faced by the Agri-industry of developing economies are as below:

3.1 Utilization of energy

The modernization of the agriculture sector in developing economies is severely affected by the inefficient utilization of energy resources (Ali, 2019). There is a significant and positive association between per capita energy and productivity (Klass, 1998). The efficient utilization of energy helps the farmers to reduce their drudgery and stay engaged in a variety of agricultural and off-farm productive activities. The digitalization of the agriculture sector is likely to generate sufficient food for the entire human population (Chancellor 2001). The prevailing trends in the agriculture sector of developing nations indicate that the increasing food needs in these economics can only be addressed by efficient utilization of energy which in turn depends on the integration of digitalization of the agriculture sector. Additionally, the processes such as energy modeling can also effectively save energy resources (Bolandnazar et al., 2019; Al-Ghandoor et al., 2009; Yildizhan & Taki, 2018). Many researchers have conducted experiments on energy utilization in the agriculture industry using modeling (Taki et al., 2018; Taki & Yildizhan, 2018) ranging from geological models related to the research on natural resources to model the future energy demand (Pahlavan et al., 2012; Khoshnevisan et al., 2014). However, in the past energy researches, regression analysis was the usual modeling technique that could be used in energy researches.

3.2 Variability Management

There exists an inherent geospatial variation in the fertility of farming land (Eldridge & Beecham, 2018). Therefore, the farmers need precise information about the local climate and soil properties to effectively deal with the inherent agriculture variability of the land and achieve agriculture sustainability (Opara, 2004). Indeed, the fusion of digital cognitive solutions will take the agriculture sector beyond the feats of mechanization and automation. But still, the successful integration of these emerging digital solutions relies on educated and well-informed decisions. In other words, the agriculture industry always needs certain well-educated individuals to manage land variability using their technical agricultural knowledge and a set of available digital cognitive solutions can potentially assist farmers to meet this objective.

3.3 Farming lands

Farmers are mostly dependent on the small farming lands primarily for the supply of food, feed, and fiber, etc. in developing countries (Tilman et al., 2002). This small farming lands produce a small quantity of agriculture output (Paul & Gĩthĩnji, 2019) which indirectly hinders the farmers' financial ability to afford AI solutions for their lands. Though some resounding advancements are made in the global AI packages focused on the betterment of the agriculture sector, but the small farming lands have eluded mankind of these benefits in most of the developing nations. There is an immense need to introduce sustainable AI-based cognitive solutions in the agriculture sector and merge these solutions with other technologies including ICT, biotechnology, and nanotechnologies, etc. to resolve this problem.

3.4 Marginal land farming

Access to agricultural resources is continuously reducing due to the exploding population and poverty situation in developing countries. The agriculture sector is under constant pressure to produce surplus agriculture products for the increasing world population by over-cropping the same lands which in turn reduces the marginal productivity of the farming lands (Nayak et al., 2019). The latest technological solutions supported by AI solutions can significantly enhance the global food demand by improving the marginal productivity of the agricultural land (Altieri, 2002).

3.5 Decline in agricultural value

A consistent and comparative decline in the economic value of agriculture outcome in relation to the other sectors such as manufacturing and services raises a serious concern for the global agriculture industry (Olajide et al., 2012). The situation is more alarming in the emerging countries where 40 percent of the total economic value in the country comes from the agriculture output. Additionally, the innovative and value-adding postharvest sector has underscored the need to switch to an integrated agri-based supply chain rather than a mere commodity-based trading system. The incorporation of AI cognitive solutions in the agriculture industry of emergency economies can improve this situation to a large extent.

3.6 Poverty & food insecurity

Wide-scale poverty and food insecurity are the major concerns of emerging countries (Hasegawa et al., 2018). The inter-governmental bodies and development agencies have been emphasizing to alleviate the problems of food insecurity and poverty in the less developed countries. Almost 20 percent of the total world population lives on less than 1 US Dollar per day and 90 percent of these individuals live in Sub-Sahara African and Asia that comprise a large portion of developing nations (Thirtle et al., 2003). According to the poverty survey conducted by Wade (2001), nearly half of the global population cannot consume more than 2 US dollars on a single day. Kerr & Kolavallie (1999) has associated the integration of AI in the agriculture sector with the elimination of food insecurity and poverty in developing nations as the enhanced agriculture output will not only remove the problem of food insecurity but also increase the farmers' income. R & D activities focused on AI solutions has added around 22 percent additional value to the agriculture sector of Africa and 31 percent in Asia. But still, most of the poor farmers in the developing countries are hardly making outliving of their agriculture outcome owning to the poor yield and low per acre production. The socio-economic situation of poor farmers in developing economies raises a serious problem for them. Therefore, the cognitive AI packages must be adopted on a large scale by the farmers of developing countries to root out the wide-scale poverty and dilemma of food insecurity.

3.7 Economic globalization

The world food system is completely globalized due to the emergence of multinational and transnational food chains across the world (García-Dorado et al., 2019). These MNCs use sophisticated ICT and modern transportation infrastructures to source out the raw material from distant areas in the less developed countries. As a result, the poor farmers in emerging economies have to face severe competition from foreign players who have access to both advanced technology and government subsidiaries (Satgar, 2011). Therefore, the farmers from developing economies should also adopt digital cognitive solutions to improve their agricultural practices and to beat the local competition arising from the technologically advanced countries.

4. Emerging Computer Technologies and AI Solutions for Developing Economies

In recent times, the agriculture sector largely contributes to the gross domestic product of emerging economies (Muradi & Boz, 2018). The agriculture sector contributes to the national exchequers of the developing states from the foreign exchange being earned from the agricultural surplus exported to the developed nations. The major source of earnings for more than half of the world population living in rural areas is based on agricultural products (Shahzadi et al., 2016). Moreover, various industries in the developing nation also depend on the agriculture outcomes such as the sugar industry, textile industry, flour industry, juice industry, furniture industry & dairy farming (Agrawal et al., 2011). Most of the time, the farmers in the less developed countries face huge economic losses as they are unaware of modern technologies such as AI, lack agriculture know-how, and rely on traditional farming methods & practices (Kushkhova et al., 2019). The problems of farmers are further compounded due to low-quality seeds, water losses, irregular irrigation & harvesting, mishandling of ripened fruits, misuse of fertilizer, disease attacks, lack of necessary equipment & machinery, and attack of pests at different stages of the crop life cycle (Shahzadi et al., 2016).

Emerging computer technologies and sustainable AI solutions can bring a paradigm shift in the farming and agriculture industry as a whole (Horvath et al., 2018). AI and digital solutions will enhance the agriculture output by embedding the element of sustainability and upgrading the farming and agriculture mechanism. Digital advancements in the field of IoT, AI, and Big Data will jointly provide sustainable IT solutions for the agriculture sector. The major computer-based technologies that can be used to improve agriculture farming in the agriculture-based economies are as follows:

4.1 Internet of things (IoT)

Both structured and unstructured data can be used to make meaningful insight into the processes of food manufacturing with the help of the internet of things technology (Muangprathub et al., 2019). Digital transformation of data allows to persistently accumulates the data related to the historical weather patterns, pest infestations, soil reports, and rainfall, etc. IoT-focused advancements are expected to bring disruptive innovation in the agriculture industry of emerging economies. Proximity sensing and remote sensing are the two prominent digital solutions for the intelligent fusion of data. Remote sensing requires building sensors based on airborne or satellite systems whereas the sensors are placed in close contact with the soil in proximity sensing. Proximity sensors are placed in the intended areas of the field to gather data on soil fertility, moisture, shoot growth, climate situation, grain/fruit-bearing, profuse, leave & shoot growth as well as data on different diseases (Teal et al., 2006).

IoT devices such as transducer along with a battery supported micro-solar panel, micro-controller, and WIFI devices are mounted on a protected mini-board for designing of the remote sensing devices. The WIFI hotspot allows the remote sensing device to regularly collect the required data on predetermined intervals of time. The active WIFI hotspots also make it possible to scan and collect the data from the drones. Many informed decisions can be made by the farmers in the less developed countries by analyzing and correlating the historical data on seed quality price and weather condition etc. (Goyal, 2010).

4.2 Image-based insight

Emerging economies need precise farming techniques to develop their agriculture industry. Drone-based image technology allows scanning, in-depth analysis, and monitoring of agriculture fields (Frankelius, 2017). IoT, vision-based technology, and drone data can be coordinated to enhance the per acre agriculture yield. The drone images generate certain real-time alerts that in turn accelerate the precise farming. Technology giant Aerial Tronics uses visual recognition of APIs in drones and the IoT platform of the IBM Watson for real time analysis of images. Computer vision technology can be used in different areas of the agriculture sector to improve the farming mechanism. For instance, it helps to detect the potential diseases in plants and crops by segmenting the pre-processed leaf images into diseased and non-diseased portions. The segmented diseased leaf parts are then forwarded to laboratories for medical diagnosis. This process helps to identify different pests and nutritional deficiencies in the crops.

Similarly, the image-based insight also assists to assess the extent of crop readiness and level of fruit ripening by capturing crop images in different stages through white UV-A light. As a result, the farmers can exercise a proactive approach by putting the fruits into separate stacks before sending them to vendors. Moreover, the use of high-quality images also supports the process of agriculture field management through generating field maps and recognizing the field areas that need fertilizer, water, or pesticides (Goap et al., 2018). This process allows the farmers to make some real-time estimates during the cultivation period and optimize the allocation of already scarce resources in emerging agriculture economies.

4.3 Digital cognitive solution

Farmers can make informed decisions based on the information derived through digital solutions such as soil condition, infestation, weather estimation, and multiple other parameters (Dharmaraj & Vijayanand, 2018). They are also in a better position to make personalized choices that adhere to the best farming practices, location conditions, and past farming experience. Besides, the external factors such as consumer needs, marketplace trends, prices are also effectively estimated through digital cognitive solutions that further improve the accuracy of farmers' decisions (Cheema et al., 2018).

4.4 Hyperspectral imaging

Advanced technologies such as hyperspectral imaging combined with 3-D laser scanning could prove very beneficial in developing robust crop metrics across a hundred acres of farming land (Lawrence et al., 2003). The life cycle of a crop can also be monitored and any anomalies in the generation period can be timely reported with the aid of hyperspectral imaging (Ota & Kawano, 2019). Hence, the AI-supported digital cognitive solutions can revolutionize the manner farmers use to monitor their farmlands in developing countries from both time and effort perspectives.

4.5 Drone-based technology

Drone technology is a modern AI innovation that can potentially resolve a series of agriculture concerns of developing countries by providing several sustainable high-tech makeovers. Drone technology has multiple productive applications in the crop cycle (Trippichio et al., 2015). It generates precise and reliable maps for performing the early soil analysis through the collection of the necessary data related to the seed planting, irrigation, and nitrogen levels. Furthermore, drone technology can be used to do five times faster aerial spraying than normal spraying (Mogili & Deepak, 2018). The inefficiencies in the crop development stages can also be identified through drone technology by generating drone-based time-series animation graphics. Likewise, this technology can also inform the farmers about possible crop diseases by tracking the changes and scanning the crops through near-infrared and visible lights.

5. Findings & Conclusion

This study has performed a systematic review with the purpose to identify the major trends, challenges, limitations, and the applicability of AI in the agricultural industry in developing countries. 87 research papers are reviewed for the chosen last 20 years from 2000 to 2019 inclusive with varying approaches to treat different aspects (i.e. detection, grain quality, diseases, etc.) of different contexts related to agricultural issues. Although, vast research on artificial intelligence and the agriculture industry is on the way in developing countries still there is a lack of enough AI and cognitive solutions in the agriculture sector of emerging economies due to the high cost of available AI cognitive solutions.

The enormous scope of AI in the agriculture sector can be only exploited by integrating robust cognitive packages in agro-based economies. Today, sectors, sub-sectors, and segments where AI is implemented shows higher growth parameters, rate of production, productivity, economic success, lower costs, etc. The cognitive solutions enable the farmers to enhance agriculture production and sustainably handle the potential shifts and changes in the external environment. The sustainability-focused AI solutions can positively transform the agriculture sector of the developing economies into a modern industry by producing the agriculture products on a wide scale and allowing the farmers to improve necessary agriculture practices such as crop cultivation, harvesting, irrigation, and other agriculture practices.

Sustainable AI solutions can also improve real-time decision making by collecting proper contextual data and utilizing the appropriate cognitive models. The food insecurity catastrophe in third-world countries can be only evaded with the help of sustainable technological advancement in agriculture farming practices. The future of the agriculture industry in developing nations largely depends on adapting sustainable AI solutions. Furthermore, agriculture practices in developing countries reveal that there are major drawbacks in the cognitive solutions used for agricultural purposes.

Human expertise is not only scarce but also very costly in the agriculture sector of emerging countries whereas the technically skilled human resource is using several cognitive packages to increase their agriculture output by many folds. The farmers in developing countries are also compelled to sell their primary agricultural output at very cheap prices due to their low bargaining situation. Therefore, this study concludes that there is a need to actively introduce the concept of AI in the agriculture sector of the developing economies by making AI more viable and affordable for the farming community in the developing nations. The adoption of artificial intelligence in the agriculture sectors of emerging countries would substantially lower the acreage, labor number in the fields, environmental deterioration, and other complicated issues. The transfer of sustainable AI solutions to the developing nations will also improve the food distribution mechanism besides enhancing the production of global food.

This research study has put forward several research implications based on its findings. Firstly, advanced agriculture AI architecture is needed in the developing nations, which must be formed based on the block principle and these blocks should be assembled on a holistic basis. Secondly, there is an absence of an original version of the AI system in the emerging economies. This does not mean that people in developing economies do not develop programs at all, but foreign partners offer most of the digital programs that are very highly-priced. The foreign firms also mostly establish the architecture of AI in the agriculture industry of developing states. Therefore, we should recognize it as such and try to go out or get around it. Finally, there is a need to create a centralized AI model for the agriculture industry of emerging economies. This will integrate AI into a single system that could be used in various objects, enterprises, and concerns of the agriculture industry. As a result, a "single mind" will be created which can be easily observed, coordinated, and controlled across the agriculture industry.

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