Artificial intelligence to improve food and agricultural sector

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ABSTRACT

An enormous problem for the agri-food sector will be meeting the demands of a global population predicted to surpass 9 billion by the year 2050, which would need a 70% boost in agricultural and food output. Such a need is difficult to meet in the absence of computational tools and a plan for predicting, especially in light of resource shortages, climate change, the COVID-19 pandemic, and very hard socioeconomic circumstances. In this research, we highlight the significance of AI and ML as a predictive transdisciplinary approach to enhancing the food and agricultural industry. However, stakeholders should be aware of a few limitations that we highlight.

1. Introduction

2. In order to feed the world's estimated 9–10 billion people by the year 2050, food production would need to rise by 60–110 percent. Therefore, in order to provide food security and the elimination of hunger for the ever-growing population, the sustainability of the agricultural sector is crucial. Furthermore, a well-documented traceability system is now necessary for quality control in the food chain as a result of several food safety scandals and accidents, such as dioxin in chicken and bovine spongiform encephalopathy [3]. In addition, the future years will bring significant difficulties related to weather and climate change, as well as sustainable water management in light of water shortages. Because of these reasons, it is critical to immediately begin planning a transition away from the present paradigm of increased agricultural productivity and towards sustainable agriculture. Supporting farmers and stakeholders in making more informed decisions about sustainable agricultural practices—including the use of digital technologies like the Internet of Things (IoT), artificial intelligence (AI), and cloud computing—is essential for anticipating effective solutions. Machine learning and deep learning algorithms, two branches of artificial intelligence, are also heavily used, often in conjunction with location intelligence technology. The purpose of this review is to provide the key applications of artificial intelligence and machine learning techniques in the agri-food sector.

3. Artificial Intelligence and MachineLearning Approach

4. Machines, mostly consisting of computer systems, robots, and digital equipment, may mimic human intellect and ability processes via the use of artificial intelligence (AI) [4]. Computer vision can detect analogue-to-digital conversions like video, voice recognition and expert systems can mimic judgement, and natural language processing (NLP) can understand human verbal communication in real time. Learning, reasoning, and self-correction are the three cognitive abilities upon which AI encoding is based [5]. Learning entails acquiring data and building algorithms to transform it into actionable information. Reasoning entails selecting the most appropriate algorithm to achieve a desired outcome. Finally, self-correction entails continuously adjusting algorithms to optimise their accuracy. Many of the fastest-growing industries are using AI techniques, including finance, healthcare, retail, pharmaceutical research, intelligent process automation, marketing, and pharmaceutical research. An important part of artificial intelligence (AI) is machine learning (ML), which gives humans a leg up when it comes to brainstorming and

efficiently. To learn from datasets and create data-driven predictions/decisions, ML employs statistical and mathematical methodologies. For this, there are a number of options. Two systems may be used to make a general distinction: symbolic techniques, which explicitly describe the induced rules and instances, and sub-symbolic approaches, which use artificial neural networks (ANNs). There are three main branches of machine learning: supervised, unsupervised, and reinforcement learning. This strategy aims to map the variables to the desired output variable in accordance with supervised learning [6]. By combining the labelled data with what is already known about the input and output variables, the predictive model may be built. Supervised learning methods make use of a wide variety of algorithms, the most common of which being regression analysis, decision trees, and Bayesian networks. Unsupervised learning makes use of unlabeled datasets and does not need any previous information about the input or output variables; it encompasses methods like Artificial Neural Networks (ANNs), clustering, genetic algorithms, and deep learning. A good example of an unsupervised machine learning approach is the one described by Jordan and Mitchell [7]; it is mostly used for dimensionality reduction and exploratory data analysis, and it finds latent patterns in unlabeled datasets. The third kind of machine learning job is reinforcement learning, which encompasses a wide range of applications, including Q-learning and deep Q-learning, which are used for machine skill acquisition, robot navigation, and real-time decision making. Here, the learner engages in environmental data collection as part of an ML assignment, which merges the training and testing phases. The learner has a conflict between exploring and exploiting the environment since he obtains rewards for his behaviours. Instead of relying on previously acquired knowledge, the learner must go into uncharted territory in order to amass additional data [8]. Artificial intelligence has only recently made its way into the agri-food industry. In reality, several agri-food applications and supply chain stages may benefit greatly from AI approaches, which provide substantial contributions and aid with understanding model identification, service development, and decision-making processes. Artificial intelligence (AI) in agriculture aims to improve productivity while preserving resources [4]. AI tools can evaluate performance, classify patterns, and predict unexpected problems or phenomena. This helps with understanding agricultural fields, identifying pests and the best way to treat them, managing irrigation and water consumption through smart irrigation systems, and more. In order to improve the management of crops and animals, scientists are using sensors and remote sensing to evaluate biotic and abiotic components [4, 9]. Furthermore, the agri-food industry and allied businesses stand to gain a great deal from the use of artificial intelligence (AI). To start, AI is making farming more efficient in all stages, from planting seeds to harvesting and selling finished goods. It's also helping with quality control, identifying and eliminating unhealthy crops, and increasing the likelihood of healthy crop output.

uses, including automatically adjusting machines for weather prediction and pest or disease identification with a 98% success rate. Indeed, a recent study by Sujatha et al. [10] evaluated the efficacy of ML and DL approaches in detecting and identifying the leaf disease of citrus plants. They demonstrated that, when it came to accurately diagnosing diseases, the VGG-16 deep learning algorithm performed the best. Secondly, advancements in AI have helped agro-based businesses run more efficiently by enhancing crop management practices. This has allowed many tech companies to invest in algorithms that are becoming useful in agriculture and has also helped farmers overcome challenges like climate variation and weed and pest infestations, which decrease yields. By utilising US Midwest corn yield data, Crane-Droesch [11] demonstrated that their innovative modelling approach—which they call semiparametric neural networks (SNNs)—outperformed classical statistical methods and completely nonparametric neural networks when it came to predicting yields of years withheld during model training. Thirdly, farmers can have access to up-to-date weather forecasting data through AI tools. This data helps farmers increase yields and profits without putting their crops at risk. After analysing the data, farmers can learn from their mistakes and make prudent decisions with precision. It is worth noting that Fente and Singh [12] utilised the Indian climate data centre to gather various weather parameters such as temperature, precipitation, wind speed, pressure, dew point visibility, and humidity. They then used a recurrent neural network (RNN) with the long-short-term memory (LSTM) technique to implement a weather forecasting model. Results were far more accurate than with previous weather predicting methods, they found. Lastly, artificial intelligence methods can track the well-being of soils and their management. This is achieved by analysing patterns in farming, which includes soil defects, plant pests, and diseases, as well as by capturing images of the soil using a camera recognition tool or a deep learning-based tool. Actually, Suchithra and Pai [13] used the Extreme Learning Machine (ELM) method with various activation functions, including hard limit, sine-squared, triangular basis, hyperbolic tangent, and gaussian radial basis, to classify and forecast the soil fertility indices and pH levels of the soil in the north central laterite Indian region of Kerala. In four out of five cases, they found that the hyperbolic tangent followed by the Gaussian radical basis function had the best result (80% accuracy rate computations in every problem). Nevertheless, the hyperbolic tangent had the highest performance (90%) in the pH classification task, whereas the gaussian radial basis provided middling results. Fifthly, reducing pesticide consumption is a major functional benefit of AI technology employment that helps safeguard the environment. For instance, artificial intelligence methods may be used to control weeds more efficiently and precisely by By using robots, computer vision, and machine learning, farmers would be able to precisely target weeds with chemical sprays, significantly reducing the need to treat the whole field. Consequently, farmers are finding more effective ways to preserve their crops from weeds with the aid of AI technologies. In conclusion, the agri-food supply chain can benefit from advanced AI-based technologies in a number of ways, including a decrease in the costs associated with employee training, a shortening of problem-solving times, a decrease in the amount of human error, a decrease in the need for human intervention, and the provision of automated goods, accurate, and robust decision-making at the right time and at a low cost [14].

5. Artificial Intelligence Technology and Application to Improve Agriculture andFood Industries

6. Preproduction, production, processing, and distribution are the four primary areas of the agricultural supply chain where ML algorithms are now seeing increased application [15]. The usage of ML technologies is very prevalent in the preproduction phase, particularly in the areas of agricultural yield prediction, soil property analysis, and irrigation needs assessment. Detecting diseases and predicting the weather are two potential applications of ML in the subsequent manufacturing phase. The third processing cluster makes use of ML techniques, particularly for estimating production planning in order to achieve a high and safe product quality. Storage, transportation, and customer analysis are three areas where the distribution cluster might benefit from ML algorithms. At the very beginning of the supply chain for agricultural products is the preproduction cluster. Soil characteristics, irrigation requirements, and agricultural production forecasting are its primary foci. The significance of agricultural yield output in

bolstering plant management has been highlighted by several studies. In reality, these precision agriculture tools seek to improve smart farming practices by using input data (equipment requirements, nutrients, and fertilisers) to predict efficient models based on ML algorithms. The goal is to get stakeholders and farmers to support ideal decisions in crop yield forecasting. Predicting agricultural yields has recently made use of many ML algorithms, including Bayesian networks, decision trees, clustering, deep learning, and ANN [16–18]. Various ML algorithms are used to learn soil parameters in accordance with the prediction of soil management properties. Morellos et al. [19] examined 140 soil samples using the LS-SVM (least-squares support vector machine) approach. The SaE (self-adpative evolutionary) ML algorithm was used by Nahvi et al. [20] to enhance the performance of the ELM architecture in order to predict the soil temperature on a daily basis. On top of that, the CSM (Crop Selection Method) was suggested by Kumar et al. [21] as a fresh approach to crop selection issues and the improvement of net yield rates throughout the growing season. Furthermore, 18 table olive cultivars from throughout the globe were examined by Ben Ayed et al. [16] utilising morphological, biological, and physicochemical measures, as well as the

A Bayesian network was used to investigate how these factors affected tolerance, productivity, and oil content. They found that the oil concentration was significantly affected by the crop's tolerance. In the preproduction cluster, irrigation management is another critical component that affects crop quality and yield. To improve irrigation decisions (when, where, and how much water to apply), researchers simulated and optimised models using data on soil moisture, precipitation, evaporation, and weather predictions based on machine learning algorithms [22]. Actually, Arvind et al. [23] shown that it was efficient to use ML algorithms in conjunction with other technologies like sensors, Zigbee, and the Arduino microcontroller to forecast and deal with drought scenarios. To optimise water resources in a smart farm, Cruz et al. [24] used artificial neural network (ANN) feed-forward and back-propagation technology. An artificial intelligence tool, Choudhary et al. [25] used PLSR and other regression algorithms in conjunction with sensors to gather data and Internet of things hardware to improve efficiency and economic feasibility.

The second step of the agricultural supply chain is the production cluster. The crop production process is influenced by and heavily influenced by a multitude of elements. Some of them include: managing crop quality, harvesting, and weather predictions (sunlight, rainfall, humidity, etc.). Others include protecting crops from biotic stress factors (weeds, infections, etc.) and abiotic stress factors (nutrient and water deficiency, etc.). For example, various ML algorithms are used to model effective weather prediction systems, crop protection systems, weed detection systems, crop quality management systems, and harvesting systems. These systems use ANN, deep learning, decision trees, ensemble learning, and instance-based learning, clustering and regression, deep neural networks, and data mining techniques like k-means clustering, k-nearest neighbour, ANN, and support vector machines. It is also common practice to use ML algorithms to foretell how a crop's colour will change throughout the harvest stage, the last horticultural step before harvests ripen. Several research groups have employed ML algorithms to forecast when fruits will ripen and how mature they will be. For example, Gao et al. [31] classified strawberries into early-ripe and ripe stages with a classification accuracy of 98.6 percent using hyperspectral datasets and the AlexNet CNN deep learning model. Third in the food production supply chain is the processing cluster. A wide variety of processing methods, including refrigeration, grinding, smoking, boiling, and drying, are used to transform agricultural goods. While avoiding resource overutilization, selecting effective combination parameters during processing leads to a food product of good quality and quantity. Several food processing companies have used ML-based software algorithms to accomplish this aim. Common machine learning methods include genetic algorithms, artificial neural networks (ANNs), clustering, and Bayesian networks [32].

According to what Arora and Mangipudi [33] said, support vector machines already exist.

employing support vector machines (SVM) and artificial neural networks (ANN) to identify nitrosamine in red meat samples; the results of the prediction modelling showed that the deep learning model achieved the best testing accuracy. Also, to find out what kind of milk it was and if it was legitimate, Farah et al. [34] employed ML methods such gradient boosting machine, random forest, RF, multilayer perceptron, MLP, and GBM in conjunction with differential scanning calorimetry. When it came to classifying contaminated samples, the most effective machine learning algorithms were GBM and MLP, which achieved 100% accuracy. The agricultural supply chain culminates in the distribution cluster. This step bridges the gap between the first stages of food production and processing and their ultimate destination for consumption. Transportation, storage, consumer analytics, and inventory management are some of the potential applications of ML algorithms. Genetic algorithms, clustering, and regression are the most common algorithms utilised in the transit and storage processes. Improved product quality preservation, guaranteed product safety, and damage minimization via product tracking are the goals of these predictive approaches [16]. In the food retailing sector, ML methods like ANN and deep learning are utilised for consumer analytics to anticipate demand, perception, and purchasing behaviour. Using ML genetic algorithms aids in inventory management by forecasting daily demand and preventing issues with inventory [35]. Robotics and mechatronics [2], drones [2, 36], GISs [37], blockchain (BC) [38], and satellite guidance [2] are only a few examples of the many AI-applied technologies used in the agri-food business. Providing a systematic process where connection, automation, accuracy, monitoring, and digitalization are common, these elements are classified as sensing, smart, and sustainable technologies by Miranda et al. [39]. The goal of smart mechanisation, robotics, and mechatronics in farming is to alleviate manual labour and cut down on inputs by means of very intelligent and autonomous equipment [2]. A new age has dawned in agriculture and the food industry, marked by the transition from manual labour to mechanisation, cutting-edge technology, computerised analysis and decision-making, and an increase in both agricultural output and efficiency [2]. Revolutionary machines, commonly referred to as "agribots," are being used in agriculture for a wide range of tasks, including but not limited to: tilling the soil, planting seeds, treating weeds and pests, watering, fertilising, and, finally, harvesting grain and fruit with little human intervention and energy expenditure [2, 44-47]. From herbicide application in the soil to pesticide application on the plants, physiological control and monitoring, and finally, harvest time determination are all steps that may be accomplished with the use of agricultural drones as a full crop management system [2, 36, 48-51]. Now farmers may use agricultural drones to film, take pictures, and create real-time maps of their fields and plants to aid in management decision-making[2, 48, 52–56]. Drones can also deliver water, fertilisers, herbicides, and insecticides. Drones are now often used by farmers to keep tabs on their animals, checking for signs of disease, injuries, and even pregnancy [57]. Throughout the year 2019, the

In contrast to the predicted value of the robot and agricultural drone industry of USD 23 billion in 2028 [59, 60], the value of the agriculture drone market was around USD one million in 2017 and is anticipated to reach USD 3.7 million in 2027 [58]. Crop management, irrigation control, yield estimation, disease and weed control, farming automation, livestock monitoring, vegetation mapping, erosion, and land degradation forecast are some of the many agricultural applications of GIS, which is based on satellite-based geospatial technology [37, 61–68]. Therefore, GIS is a good fit for precision agriculture, real-time control, and awareness-raising, and it helps a lot with meeting the demands of the ever-increasing food need. Another technology that addresses consumer concerns about the provenance, quality, and most importantly, safety of food is blockchain. By eliminating the need for a central server or single point of control and replacing it with a shared database that all users can access and participate in transactions, BC ensures that the entire food product supply chain—from farm to fork—is transparent, trustworthy, certified, and traceable [38, 69–79]. A plethora of organisations, consortia, and platforms came into existence in this context [79] due to the fact that digital and computerised traceability of the whole food supply chain would enable detection of deficiency, contamination, and adulteration of the product, hence optimising its quality and safety. The global agri-food market for BC was valued at around USD 133 million in 2020, and by 2025, experts predict it will have grown to over USD 950 million [69]. The use of satellite-guided technology in agriculture has vastly enhanced farm monitoring, crop husbandry, irrigation, disease and weed control, yield calculation, mapping agricultural zones, soil management, and harvesting [2, 80–88]. Therefore, in the late 1900s, a single farmer could produce food grains for 128 people. This ratio will certainly rise in the future thanks to smart agriculture [2].

7. Limits and Drawbacks of AI and ML

8. Nevertheless, there are a few downsides to AI technology that pose problems, even if it offers many benefits. Firstly, the most pressing societal issue is the potential danger of unemployment; smart machines and robots have the potential to replace most monotonous chores and jobs; as a result, human intervention is decreasing, which poses a serious threat to employment standards. Another technical hurdle is that machines can only do the duties for which they were designed or programmed; when asked to do anything beyond their programming, they often malfunction or provide useless results. Also, AI is constantly evolving, so the hardware and software need to be updated to meet the latest requirements. However, the high costs of creating and maintaining smart machines and supercomputers could be seen as technological limits of AI technologies. Repairing and maintaining machines may be rather costly. They are incredibly complicated machines, which means that their creation is quite expensive. Another concern with these applications is their expensive pricing, which might lead to a rise in of the products. Moreover, beyond the opportunities afforded by smart and computerized technologies, some risks and apprehensions could be posed for sustainability, particularly the massive energy consumption, e-waste problem, market concentration, job displacement, and even the ethical framework [79, 89].

9. Conclusions

10. There are few sectors more important to human survival as the agricultural and food processing industries. In order for the final consumer to have their hands on agricultural goods, they must first pass through four distinct phases of the supply chain: preproduction, production, processing, and distribution. These phases are all part of larger multi-actor dispersed supply chains. There is an immediate need to implement digital technologies at various points in the agricultural supply chain, including the automation of farm machinery, the use of sensors and remote satellite data, artificial intelligence, machine learning, improved crop monitoring, water, and food product traceability, in order to meet the future demands of the food and agriculture industries, which are influenced by factors like climate change, population growth, technological advancement, and the condition of natural resources (water, etc.). In this paper, we show how AI and ML algorithms are being used in various parts of the agricultural supply chain, and we also show that these algorithms are definitely being used more and more to make food sectors better.

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