Artificial Intelligence and Machine Learning Applications in Agricultural Supply Chain: A Critical Commentary

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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS IN AGRICULTURAL SUPPLY CHAIN: A CRITICAL COMMENTARY

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ABSTRACT

Integration of AI and ML technologies in the agricultural supply chain (ASC) is revolutionalizing, the domain by bringing in robust monitoring and prediction as well as quick decision-making abilities. A comprehensive literature analysis of the applications of artificial intelligence methods and machine learning algorithms in the agricultural supply chain is demonstrated in this study. In order to solve complicated challenges confronted by various areas of the agricultural supply chain, this literature analysis addresses different significant works that machine learning and artificial intelligence methods are used. Different AI and ML applications were suggested for the following areas of agriculture belonging to different phases: (i) crop yield prediction, prediction of soil properties and irrigation management; (ii) weather prediction, disease detection and weed detection, (iii) demand management and production planning, (iv) transportation, storage, inventory and retailing. In order to remain unbiased and objective, different studies from different journals were analyzed for each phase. It is observed that the majority of these studies focus on crop yield and soil properties prediction. It is also inferred that artificial neural networks, support vector machines, utilization of unmanned aerial vehicles, and remote sensors are fairly popular in the agriculture discipline.

KEYWORDS:
Agricultural Supply Chain, Machine Learning, Artificial Intelligence

INTRODUCTION

Agriculture plays a crucial role in terms of many aspects. It’s pivotal for economic growth in many countries, especially for developing nations. Moreover, it is an essential factor to reduce hunger and poverty. A well organized agricultural supply chain can reduce food waste and carbon footprint; enable food security, a sustainable food system, and well-preserved nature.

Several studies reveal that a population increase for the coming decades is estimated. As a result of this, a rise in global food demand is expected. Some updates should be made in the production processes of agriculture to reduce waste and increase production levels. That is why, an intelligent platform, which has three main parts, was developed and then presented as a prototype [1]. Agricultural systems face increasing pressure to preserve sustainability, preserve the ecosystem's integrity, and natural resources during all processes [2].

Through digital technologies like AI and Machine Learning, the Internet of Things (IoT), Cloud, and Blockchain, agricultural supply chain systems are seeking to create innovation to their works [3]. A public blockchain of the agricultural supply-chain system based on the double chain was proposed [4]. An environmental monitoring system was designed for agricultural facilities [5]. A new wireless sensor network non-uniform algorithm was proposed for ecological environment monitoring [6]. AI and ML are becoming extensively used in the agricultural supply chain systems due to their strong computing power and instant monitoring ability, which humans cannot perform equally well by humans [7].

A thorough analysis of the utilization of AI and ML applications in diverse agricultural supply chain stages is explained in this study. In Section 1, five distinct phases of the agricultural supply chain, and the specific areas involved are presented. Additionally, the challenges faced by agricultural supply chain systems are discussed. In Section 2, the definition of AI and ML technologies are given. Different ML methods and their key features are outlined. In Section 3, various AI and ML technologies in the literature are reviewed for all phases of the agricultural supply chain. Finally, in Section 4, the percentage of AI and ML technologies and agricultural supply chain areas examined in this paper are analyzed through diagrams. In addition to future expectations in the field, the pros and cons of AI and ML technologies in the agricultural supply chain are discussed.

As shown below, Table 1 is created to clarify the abbreviations as a result of the vast number of abbreviations used for defining scientific language in this study.

TABLE 1
Frequently used abbreviations in this review and their explanations

Abbreviation	Explanation
ASC	Agricultural Supply Chain
AI	Artificial Intelligence
ML	Machine Learning
UAV	Unmanned Aerial Vehicle
SLR	Systematic Literature Review
ANN	Artificial Neural Networks
SVM	Support Vector Machines
CNN	Convolutional Neuronal Networks

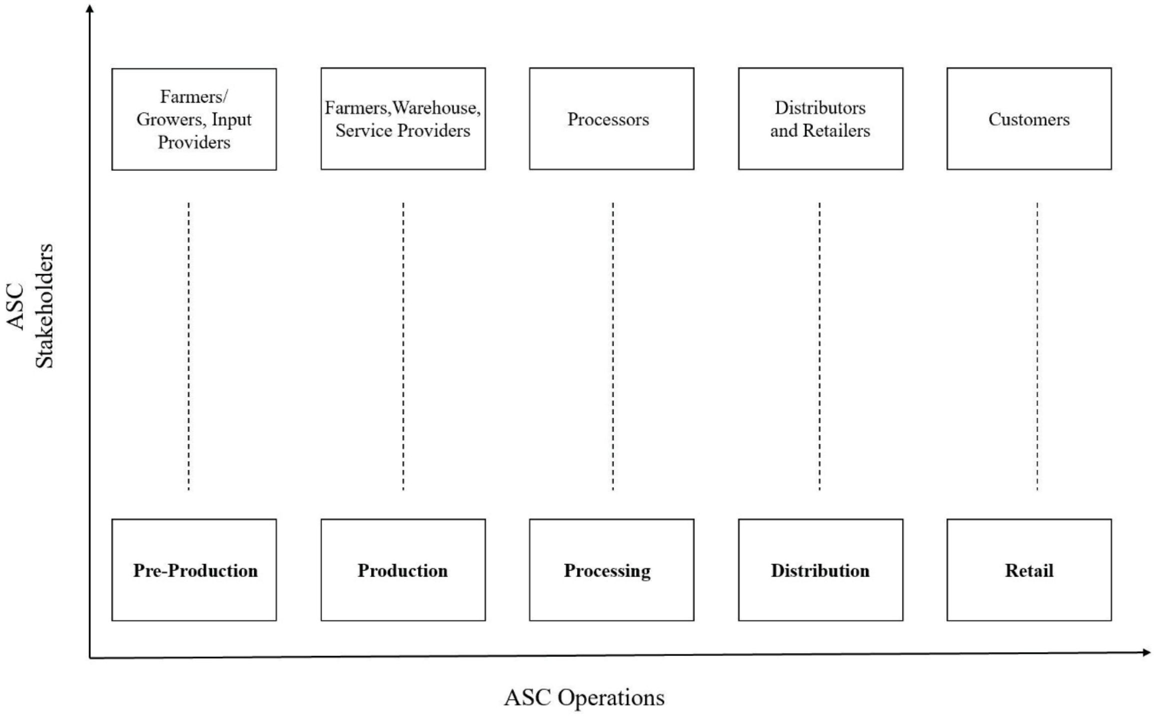

FIGURE 1
Agriculture Supply Chain Processes [8]

MATERIALS AND METHODS

In this paper, various studies were reviewed and then the most related 45 published research articles on the topic of AI and ML applications in agricultural supply chain were analyzed. The articles were sourced from different databases such as Elsevier, IEEE, Springer and Taylor. Majority of the paper that was used in this review are published in 2016 and onwards. However, a few reviews published in the early 2000s were also included in this review to observe drastic changes in the AI and ML methods used in the agricultural supply chain since then. Finally, a statistical approach was taken to analyze the percentage of different areas of the agricultural supply chain and different AI and ML methods that were discussed/used in different systematic literature reviews (SLRs). Along with proposing ways to progress the agricultural supply chain, these figures were utilized to examine the pros and cons of these applications.

AGRICULTURAL SUPPLY CHAIN

The agricultural supply chain is similar to the fast-moving consumer goods supply chains; however, it shows a difference in raw material procurement and the final product. The raw materials are acquired from the fields to be consumed by humans or animals. Figure 1 shows the agricultural supply chain processes are outlined as pre-production, production, storage, processing, retail, and distribution before the end product reaches the customers [8].

The agricultural supply chain is a complex process due to the products' perishability, high supply-demand fluctuations due to seasonality of the products, and increasing consumer awareness towards produce provenance, quality, and safety [9, 10]. The agriculture supply chain is challenged by the complexity of its operations and rapid industrialization, overpopulation, and fierce competition for natural resources [11]. Moreover, increasingly more individuals are now mindful and interested in the agricultural supply chain's social, monetary, and environmental consequences thanks to the current developments in information and communication technology. This situation has engendered an expanding burden from end consumers for growing sustainable food production and consumption policies [12].

Data-driven Agricultural Supply Chains. Bringing effective solutions to agricultural supply chains' mentioned challenges requires a better understanding of the complex agricultural ecosystems [13]. It can be achieved by using current disruptive technologies enabling continuous control of different operations and physical environments within the agricultural supply chain [14].

Wireless sensor technologies empowered by the artificial intelligence and machine learning can address the critical challenges faced by the agricultural supply chain. As large volumes of data are generated throughout the ASCs, the analysis of these big volumes of data through machine learning would help farmers and organizations to gain valuable insights, thereby improving productivity through data-driven decision-making [12].

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

AI aims to develop a technology that functions similar to the human brain [15, 16]. The examination of how individuals act while solving a problem or making a decision conceptualizes this technology, and then intelligent software and systems are developed. Training data promoted this software, these intelligent instruments ensure the preferred yield for each input just as the human brain does [17]. Machine learning and deep learning, which have vast domain areas, are the basic elements of AI [18, 19, 20, 21]. Although machine learning can learn from data, artificial intelligence tackles with intelligent machines and programs. Moreover, the mastering of deep neural networks is DL [22, 23].

Machine Learning Terminology and Definitions. ML methodologies provide a learning mechanism that seeks to learn from experience, from training results to executing a task. The efficiency of the model is assessed by various statistical measures that change over time with practice. Using the knowledge acquired throughout the training process, the learned model can identify, forecast, or cluster new and previously unknown data (testing data) at the end of the learning process. [24]. A characteristic ML process is demonstrated in Figure 2.

Depending on the learning type (supervised/unsupervised), the learning models (classification, Regression, Clustering, and dimensional reduction), or the learning models applied to execute the task, ML models are typically categorized into various groups [24].

Machine Learning Techniques. The presented ML models are clarified and restricted to those used in the works introduced in this study.

1.Regression. The backbone of the supervised learning model is Regression. Supervised learning models seek to forecast output variables depending on input variables that are known or previously labelled. Mostly used supervised learning algorithms involve linear Regression and logistic regression [25] in addition to step-by-step Regression [26]. Ordinary least squares Regression [27], multivariate adaptive regression splines [28], multiple linear regression, cubist [29], and locally estimated scatterplot smoothing [30] are involved in more complicated regression algorithms that have been progressed.

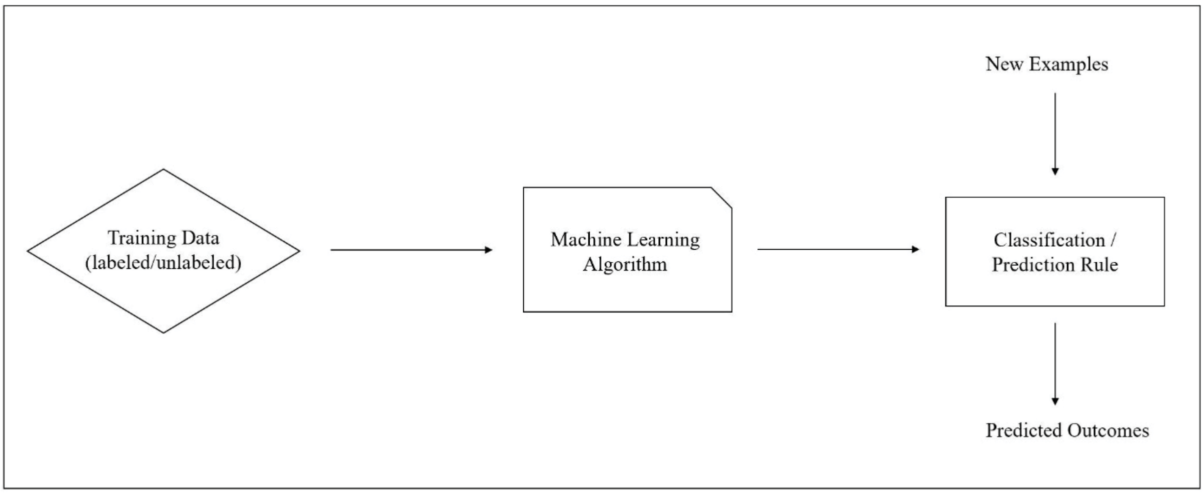

FIGURE 2
A typical ML process

2.Clustering. Clustering [31] is utilized to seek natural groupings of data and patterns within the data, and it is an unsupervised learning model. K-means technique [32], the hierarchical technique [33], and the expectation-maximization technique [34] are included in clustering techniques.

3.Bayesian Models. Bayesian models are an organization of probabilistic graphical models where the research is carried out in the sense of Bayesian inference. Bayesian models can solve problems of classification or Regression and are part of the supervised learning classification. Some of the most utilized algorithms in the literature are Naive Bayes [35], Gaussian Naive Bayes, Multinomial Naive Bayes, Bayesian Network [36], a combination of Gaussians [37], and Bayesian Belief Network [38].

4.Decision Trees. Decision trees consist of a tree-like architecture[39] and are a classification or regression model. Decision trees progressively partition the dataset into smaller homogeneous subsets, thus creating a similar tree graph simultaneously. Whereas each branch stands for the product of this comparison, each internal node in the tree signifies a separate pairwise comparison of a given element. Leaf nodes following the path from the root to leaf stand for the final decision or prediction made after. Classification and regression trees[40], the chi-square automatic interaction detector[41], and the iterative dichotomiser[42] is the most commonly used learning algorithms in this classification.

5.Artificial Neural Networks. Artificial neural networks (ANNs), are split into two sections: "Traditional ANNs" and "Deep ANNs". ANNs emulate the human brain's dynamic functionalities, just as pattern generation, preparation, and judgments, cognition [43]. There are billions of neurons in our brains and, they transport and process this information among themselves. Similarly, an ANN of interconnected processing units grouped within a particular framework is created.

ANN includes numerous nodes in several different layers, including an input layer, in which the data is introduced into the system, forms the initial layer, the last layer is the output layer in which the prediction is gained. Between the initial and the final layers, there are many secret layers in which the learning processes occur. Just as the hidden layer becomes more, the algorithm becomes more complicated.

ANNs have supervised models that are commonly used to deal with regression and classification issues. Radial base function networks [44], perceptron algorithms [45], backpropagation [46], and resilient backpropagation [47] are the most widely utilized models in ANNs [48].

Furthermore, it is also found that counter propagation algorithms, adaptive-neuro fuzzy inference systems [49], autoencoder, XY-Fusion and supervised Kohonen networks [50], Hopfield networks [51], multilayer perceptron [52], self-organizing maps [53], extreme learning machines [54], generalized regression neural networks [55], ensemble neural networks, and self-adaptive evolutionary extreme learning machines are ambiguously used as ANN-based learning algorithms [56].

Deep Neural networks (DNN) [57] are a comparatively recent ML field and can be viewed as multi-layered ANNs that can be utilized as models that are either supervised, partial, or unattended. The convolutional neural network (CNN), which extracts maps by creating convolutions in the image domain is one of the most used DNN models [24].

6.Support Vector Machines. Support Vector Machines (SVMs) are binary classifier models that create a linear separating hyperplane to classify data instances. Classification, Regression, and clustering problems are discussed using SVMs. Support vector regression, least squares support vector machine, and successive projection algorithm-support vector machine exist in the most widely used SVM algorithms. SVMs struggle with the overfitting problem in high-dimensional spaces based on global optimization, making it more attractive to numerous works [58, 59]. Consequently, SVMs efficiency can also be improved by kernel tricks, which reconstruct the original feature space into a feature space of a higher dimension [24].

7.Ensemble Learning. Ensemble learning (EL) blends many simple evaluators' forecasts with a particular learning algorithm to increase one estimator's generalizability. Every grouping that is trained represents a different hypothesis, and EL models enable the hybridization of these hypotheses. As such, it yields better predictive results regardless of the diversity among the single models. Decision trees, boosting and bagging implementations [60], AdaBoost [61], and bootstrap aggregating or bagging algorithms[62] are some examples that are used in ensemble learning.

8.Optimization and Heuristics. Optimization and Heuristic algorithms are not classified under machine learning algorithms. However, this section mentioned this in this review since optimization and heuristic models are widely used along with machine learning models to improve their performance and find the best performing result. Some of the optimization and heuristic algorithms mentioned in this review are the genetic algorithm, bee algorithm, particle swarm optimization, and simulated annealing algorithm.

AI AND ML APPLICATIONS IN AGRICULTURE SUPPLY CHAIN AREAS

As previously mentioned in Section 1, the agricultural supply chain is not a smooth-running business due to its complex nature and faces many challenges daily [63]. In this review, the areas of the agricultural supply chain are investigated, and the ones that face challenges daily the most are analyzed. As Figure 3 shows, some fields involved in pre-production, production, manufacturing, and distribution are soil properties and irrigation management, crop yield forecasting, weather monitoring, detection of illness, weed identification, livestock management, and nourishment management; demand management, planning of production, quality management; shipping, and transportation, stock, merchandising and market research.

To face the challenges of the supply chain for agriculture, the utilisation of AI and machine learning in this sector is extremely necessary since it can instantly gather hundreds of data in all segments of the chain and easily evaluate it. The use of the automation system in agriculture enables the continuous movement of products on the conveyor belt while collecting and processing data. Thanks to these systems, labour cost and waste can be minimized dramatically [7].

For every four phases illustrated in Figure 3, the implementation of AI and ML technologies in the agriculture supply chain will be addressed in this section. It should be noted that this review will only focus on the specific areas in these four faces that are facing challenges the most.

Prediction of Crop Yield. Crop yield prediction is the main challenge in terms of addressing food security. Crop yield estimation targets accurately predicting crop yields well before harvesting. Agricultural monitoring can increase food production, especially in developing countries, and support humanitarian efforts considering climate change and droughts [64]. Machine learning approaches are critical tools for crop yield prediction and making insightful decisions on what crops to grow and what kind of actions to take during the crops' growing season. After comprehensive research, it is observed that different machine learning algorithms have been used in literature to support crop yield prediction. ANN algorithm was used to model and predict crop yield by considering different weather conditions in different parts of the region [65]. The forecast for crop yield has been estimated using deep learning and machine learning. The benefits of deep learning for agricultural yield predictions were highlighted [66]. Moreover, neural networks were used to predict rice production yield. The factors, which are affecting the rice crop yield for different districts in India, were investigated [67]. Crop yields prediction was made by using publicly available remote sensing data [68]. An approach, which uses different ML techniques, was highlighted to predict the category of the yield based on macro-nutrients and micro-nutrient status [69].

Prediction of Soil Properties and Irrigation Management: The dynamics of soil properties is an essential factor for sustainable land management. Therefore it requires good analysis and forecasting. Similarly, an efficient tool for managing irrigation systems is needed due to the growing demand for the agricultural supply chain due to the increasing costs of supplying water for the fields and the stochastic nature of water resources [70]. The research conducted in this review reveals that different AI and ML applications are highly beneficial in terms of providing cost-efficient, effective and quick solutions for these aspects. .The genetic algorithm is one of the machine learning applications found to be a useful optimization tool for irrigation planning [70, 71]. Models were constructed using decision trees to predict the soil properties by considering the following properties: pH, organic carbon, total phosphorus, total nitrogen, density, characteristics, and clay ingredients [72]. In mountain regions, spatial

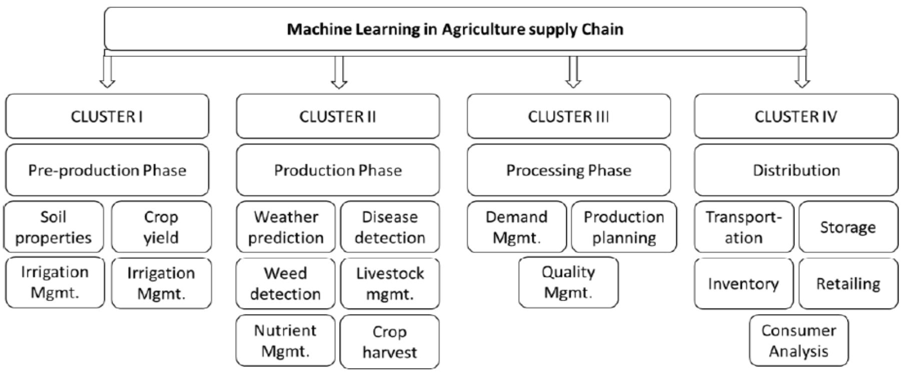

FIGURE 3
Areas of Agricultural Supply Chain belonging to Different Phases where ML Principles can be applied [12]

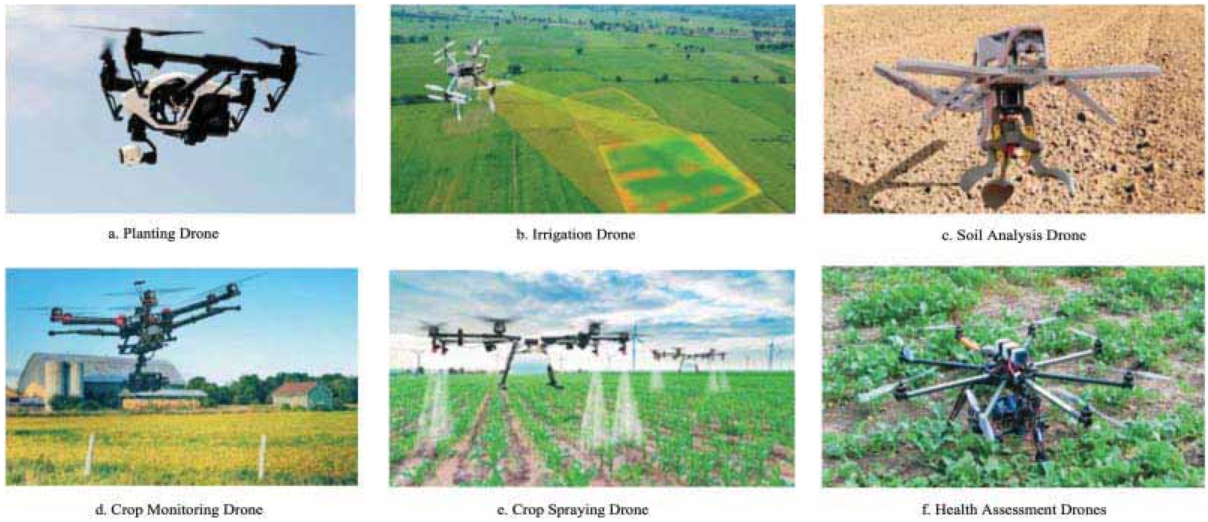

FIGURE 4
AI applications applied in some areas of the pre-production and production phases of the agricultural supply chain [77]

prediction of soil properties was examined. Support vector machines were proposed to model soil properties. It was found out that support vector machines are advantageous over other techniques as the complexity of the model is limited to the learning algorithm itself and prevents overfitting [73]. The study results show that optimized support vector machines with a simulated annealing algorithm in developing soil property prediction can be more beneficial than regression methods [74]. The use of convolution neural networks and restricted conditions of Boltzmann machines for structured output prediction have been cited for improved soil property prediction. [75].

The majority of the research conducted revealed that usage of AI is widely proposed to manage irrigation planning. It was concluded that the use of multispectral and thermal camera usage in unmanned aerial vehicles (UAVs) allows taking high-resolution images that assess the water status of crops to manage irrigation [76]. In the same vein, the use of AI-driven techniques, such as remote sensors for soil moisture ingredient detection and automated irrigation using GPS assisted by machine learning approaches such as ANN and fuzzy logic was also proposed [17].

Weather Prediction. Variability in weather can cause economic and food security risks in agriculture. Due to this dependency, accurate weather forecasts are crucial for better risk management and sustainability in agriculture. Classification and prediction of future weather were made using the back-propagation algorithm, and then they are discussed in consideration of different parameters [78]. To predict daily mean air temperatures on field-scale, a hybrid model has been built that combines a global climate model with a regularized extreme learning machine [79].

Disease Detection. Early, effective plant disease identification and diagnosis are essential to reducing qualitative and quantitative crop yield losses in crop production. Different kinds of highly sensitive sensors were recommended to identify diseases, such as spectral and thermal sensors, and fluorescence imaging [80]. The research findings reveal that robotic applications coupled with machine learning algorithms to detect plant pathology and it's management. In particular, it has been investigated that the use of platform hardware and software (UAVs, UGVs, or sensors mounted on vehicles/structures) and together with the use of profound deep neural networks have promising results in the identification of plant disease [81]. It was concluded that the combination of smartphones and deep learning made possible smartphone-assisted disease diagnosis [82]. Finally, it was found that large data sets can give a good solution by using machine learning to detect disease present in plants [83].

Weed Detection. Weeds cause many farm yield declines. The use of coevolutionary neuronal networks (CNNs) with an unpredictable dataset for weed detection of UAV-pictures was suggested as a modern, completely automated learning approach with three main phases [84]. Smart technology was developed and evaluated for precision weed management by using artificial intelligence. Neural networks were used for detection and classification. It can reduce crop damage, the number of agrochemicals as well as environmental pollution [85]. A stereo viewing method has been developed to differentiate rice plants from weeds by using artificial neural networks and distinguish two kinds of weeds in rice fields. Furthermore, to optimize the neural network for selecting the most compelling features and classifying different types of weeds respectively, particle swarm optimization (PSO) and the bee algorithm (BA) were utilized [86].

Demand Estimation, Production Planning and Quality Management. Studies have shown that farmers cannot sell their products due to lack of information or excessive supply [87]. This shows the importance of demand estimations and production planning which can be possible by using tools that enable integrating AI and machine learning and information and communication technology in the processing phase of agriculture. These technologies would allow farmers to exchange information, cooperate, get connected and, connect with the rest of the world in real-time to determine customer demand to make informed business decisions [88].

A big-data analytics-based approach, which considers Twitter data to describe the supply chain management in the food industry, was proposed. This technique involves text analysis through the use of a support vector machine and hierarchic Clustering [89].

Transportation, Storage, Inventory Management and Retailing. Due to food perishability, maintaining the quality and remaining food safety is a grave challenge during the distribution phase. To slow the biological decay process, deliver safe and high-quality foods to consumers, the required conditions need to be maintained at all times during storage, transportation, and retailing as well as keeping inventories [90]. CNN was proposed as a method of surveillance for inventory in real-time. The goal is to design and conceptualize an efficient method to count and locate items in the inventory. Better results were observed with the built algorithm [91]. An exponentially weighted moving average control chart and artificial neural network were evaluated to track the collected temperature data in cold chain management. For the estimation of temperature changes and patterns, the backpropagation neural network was used [92].

RESULTS AND DISCUSSION

This paper covers various studies. 45 of them were selected according to topic relevance. 45 research articles published in the field of possible AI and ML applications can be occupied in agriculture during the last 16 years starting from 2004 to 2020. The majority of the articles, 24.1%, are linked with AI and ML applications in predicting soil properties and irrigation management and 20.7% of them with the prediction of crop yield prediction. Followed by disease detection with 13.8% and weed detection with 13.8%. Weather prediction and other areas involved in the processing and distribution phase make up 6.9%, 10.3, and 10.3% of the areas covered in the mentioned research. These numbers are presented in Figure 5, as could be seen below.

Furthermore, based on this review, it can be concluded that increasing use of hybrid systems such as image processing along with artificial neural networks is frequently being used in agricultural systems. It is observed that ASCs increasingly use automated, precise, and accurate systems such as remote sensors and UAVs that can act much quicker in real-time compared to humans. AI and ML models used

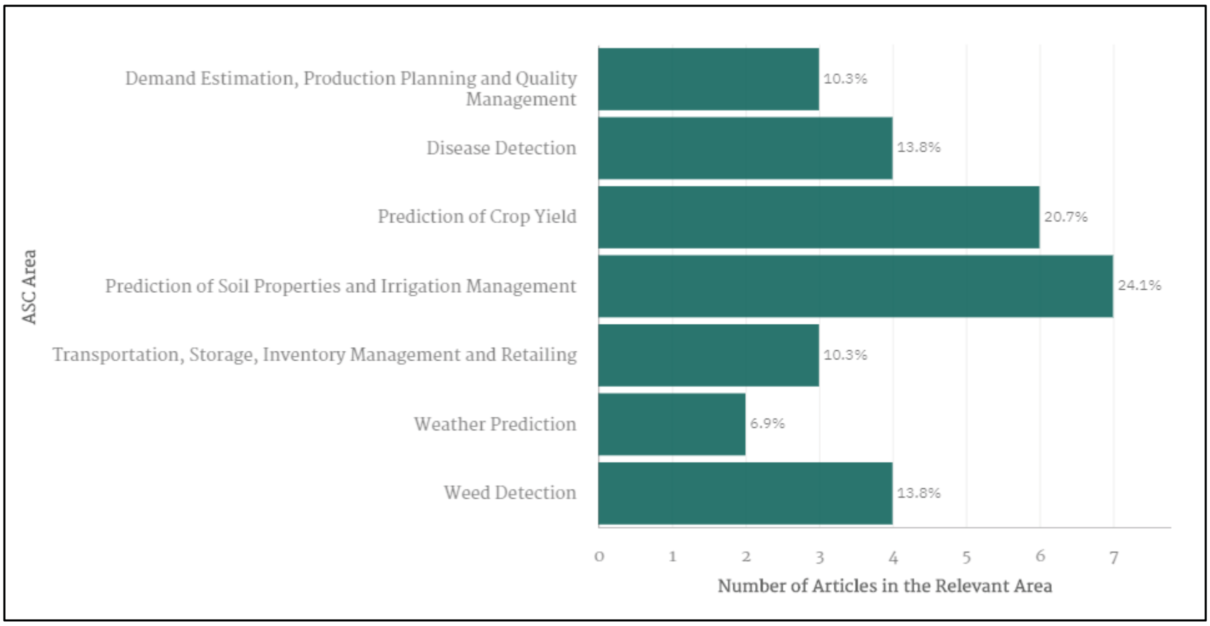

FIGURE 5
Areas of ASC mentioned in the research paper in percentages

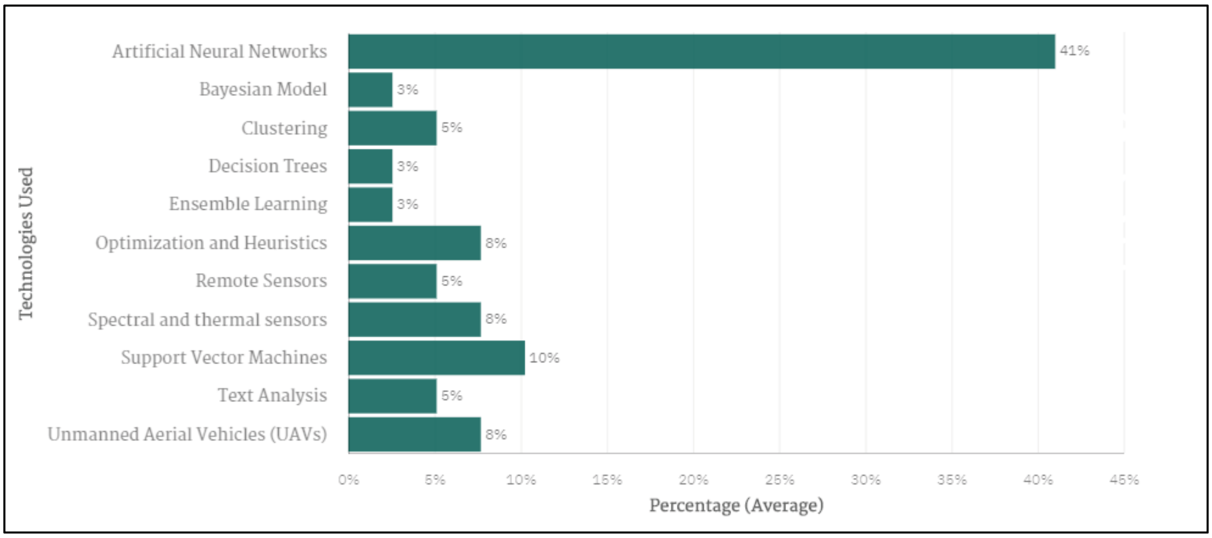

FIGURE 6
ML algorithms and AI technologies used in the research papers in this review in percentages

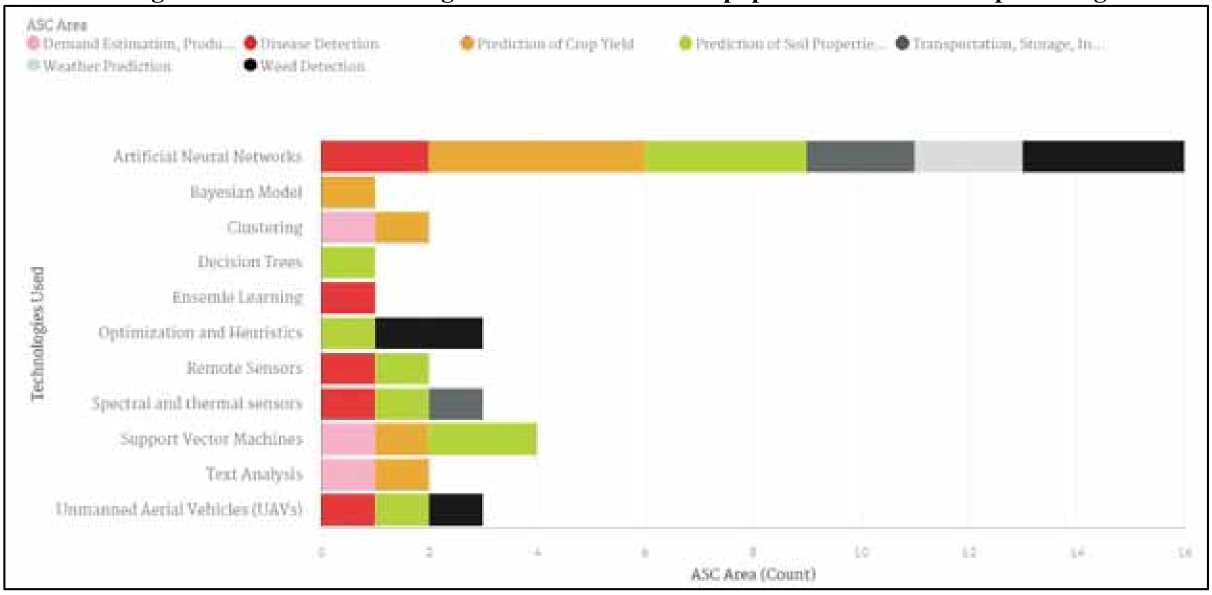

FIGURE 7
The overall sum of ML models as per each ASC sub-category

in different research are plotted in Figure 6 below. According to this figure, ANN is the most suggested method for different areas of ASC with 41% mention among the reviewed papers. SVM is the second algorithm proposed as a solution to solve challenges in different ASC areas with 10% mention. Optimization and heuristic methods were also used quite frequently along with ANNs aiming to optimize the algorithms if not frequently used alone. According to figure 6, it can also be said that UAVs and remote/thermal sensors also play an essential role in addressing challenges faced in different areas of ASC.

Finally, in Figure 7, ML and AI models used according to each sub-category in ASCs are presented.

According to this figure, it can be concluded that ANN is an algorithm that can be applied in approximately every sub-area of ASC. It can be because of its wide range of application areas as it can be used both as a supervised and unsupervised algorithm and handle large and complex data with high computational power. Secondly, it can be said that UAVs, coupled with sensor usage, seem quite advantageous in tasks that require manual human labour such as in irrigation, disease and weed detection, and prediction of soil properties. In the processing phase (demand estimation and production planning), which is symbolized by the pink colour in figure 7, methods that can help analyze customer insights and demand are employed such as text mining, Clustering, and SVM. These methods are extremely helpful in identifying patterns to understand customer behaviour and satisfaction, which can be quite useful in production planning. Finally, in the distribution phase, where transportation, storage, inventory management, and retailing are involved, ANN and optimization algorithms are mainly used along with UAVs with thermal sensors.

The above figures show that AI and ML models are widely used in ASC, especially in soil property prediction and irrigation management (24.1%), and crop yield prediction (20.7%). Due to high volumes of data-generating and real-time response and action requiring nature of ASCs, ML and AI provide a promising ground for addressing challenges that ASCs are facing, especially in the crop yield prediction area. However, in areas where extraction of further data from other resources (such as data collection in weed prediction from UAV images) is required, ML model implementations are less in use. Still, the usage of UAVs and sensors are more dominant. It can be seen in figures 5 and 7, respectively, as disease and weed prediction areas are almost addressed equally in 13.8% of the articles and addressed more by using sensors and UAVs. It can also be concluded that ANN and SVM are the most enforced ML techniques in addressing ASC challenges, especially in predicting crop yields and soil properties. Finally, it can be concluded that the decision-making process empowered with real-time on-field and customer data by usage of automated systems and ML algorithms can create the required integrity in ASCs to implement a knowledge-based agricultural supply chain system, to ultimately deliver food security and quality food to end consumers.

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