Computers and Operations Research 119 (2020) 104926

Contents lists available at ScienceDirect

Computers and Operations Research

journal homepage: www.elsevier.com/locate/cor

Technical Note

A systematic literature review on machine learning applications for sustainable agriculture supply chain performance

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ARTICLE INFO

Article history:
Received 27 February 2019
Revised 27 January 2020
Accepted 17 February 2020
Available online 24 February 2020

Keywords:
Agricultural supply chain
Machine learning
Sustainability
Smart farming
Systematic literature review

ABSTRACT

Agriculture plays an important role in sustaining all human activities. Major challenges such as overpopulation, competition for resources poses a threat to the food security of the planet. In order to tackle the ever-increasing complex problems in agricultural production systems, advancements in smart farming and precision agriculture offers important tools to address agricultural sustainability challenges. Data analytics hold the key to ensure future food security, food safety, and ecological sustainability. Disruptive information and communication technologies such as machine learning, big data analytics, cloud computing, and blockchain can address several problems such as productivity and yield improvement, water conservation, ensuring soil and plant health, and enhance environmental stewardship. The current study presents a systematic review of machine learning (ML) applications in agricultural supply chains (ASCs). Ninety three research papers were reviewed based on the applications of different ML algorithms in different phases of the ASCs. The study highlights how ASCs can benefit from ML techniques and lead to ASC sustainability. Based on the study findings an ML applications framework for sustainable ASC is proposed. The framework identifies the role of ML algorithms in providing real-time analytic insights for pro-active data-driven decision-making in the ASCs and provides the researchers, practitioners, and policymakers with guidelines on the successful management of ASCs for improved agricultural productivity and sustainability.

1. Introduction

Agriculture sustainability is the key to ensure food security and hunger eradication for the ever-growing population. It is estimated that global food production must be increased by 60–110% to feed 9–10 billion of the population by 2050 (Tilman et al., 2011; Pardey et al., 2014; Rockström et al., 2017). It is therefore required to have a strategic shift from the current paradigm of enhanced agricultural productivity to agricultural sustainability (Rockström et al., 2017). Sustainable agriculture practices not only focus on enriching agricultural productivity but also help to reduce harmful environmental impacts (Kuyper and Struik, 2014; Godfray and Garnett, 2014; Cobuloglu and Büyüktahtakın, 2015; Adnan et al., 2018). The sustainable Agriculture Supply Chains (ASCs) are knowledge-intensive and are based on information, skills, technologies, and attitudes of the supply chain partners (El Bilali and Allahyari, 2018). Knowledge transfer encourages farmers to enhance their decision to adopt sustainable agriculture practices (SAP) (Adnan et al., 2018).

Strothkämper (2016) claims that the ASCs are facing tremendous pressure to increase the farming efficiency, which is driven by the depleting rate of water and fossil fuels, shrinking availability of arable land and the increasing demand by the consumers for more transparent and sustainable food chains (Tian, 2016; Duman et al., 2017). The need for the ASCs to respond to the increas-

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https://doi.org/10.1016/j.cor.2020.104926

Table 1
Review studies on ML applications in SCM.

Authors	No. of papers reviewed	Time period	Objectives
Baryannis et al. (2019)	276	1996–2018	The study explored the extent of research in the field of supply chain risk management using artificial intelligence capabilities such as prediction, autonomous decision-making, and the ability to deal with uncertain, complex environments.
Ngai et al. (2014)	35	1994–2009	Provides a comprehensive review of research conducted in textile and apparel supply chains using artificial intelligence and decision-support systems.
Giri et al. (2019)	145	1989–2018	Highlights the impact and significance of artificial intelligence applications in apparel fashion supply chains.
Min (2010)	28		Identifies the potential supply chain areas where artificial intelligence can be deployed to solve complex problems.
Konovalenko and Ludwig (2019)	238	2005–2017	Highlights the potential machine learning and big data applications in supply chain management for reducing supply chain complexity.

ing demand and supply gaps, as well as market price fluctuations, is also identified as critical drivers of farming efficiency (Sharma et al., 2018; Patidar et al., 2018). Further, recent studies covering the sustainable aspects of inventory and transportation management concerning the perishable items may help us to understand the complexities involved in achieving sustainable ASCs. The digital technologies that include the internet of things (IoT), mobile technologies and devices, data analytics, artificial intelligence (AI), digitally delivered services, and other applications are influencing the ASCs (Kamilaris and Prenafeta-Boldú, 2018). Numerous examples demonstrate the use of digital technologies at different stages of ASC such as automation of farm machinery resulting in reduced labour input, use of sensors and remote satellite data for improved monitoring of crops, land, and water, IoT and RFID for agriculture product traceability (OECD, 2019)

As a result of going digital, a large amount of data is getting generated in the supply chains, which is useless unless it is organized, understood, and meaningful insights are gained using appropriate data analysis tools (Russo, 2015; Dubey et al., 2015). AI or cognitive-based technologies is the most transformative and impactful advanced analytics tool that can be used by the organizations for supply chain decision making (Liakos et al., 2018). AI helps computers interact, reason, and learn like human beings to enable them to perform a wide variety of cognitive tasks, usually requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages and demonstrating an ability to move and manipulate objects accordingly. Intelligent systems use a combination of big data analytics, cloud computing, machine-to-machine communication, and the IoT to operate and learn (OECD, 2017). Machine and deep learning algorithms, the subsets of AI, is widely used in combination with location intelligence technologies in ASC to identify hidden patterns in the data (Elavarasan et al., 2018). The study by Kazemi (2019) published in Forbes suggests ASC practitioners consider AI and advanced analytics as strategic investments because of the accelerating digital transformation in ASC and need to develop a competitive advantage. Patidar et al. (2018) described how information technology (IT) is impacting the expectations of farmers as well as customers and accordingly, their demand is changing.

In the past, few review studies were conducted on AI and ML applications for improving the supply chain performance, as mentioned in Table 1. These studies have focused on ML applications in the supply chain management (Min, 2010) covering specific aspects like supply chain risk management (Baryannis et al. 2019) or sectors (Ngai et al., 2014; Konovalenko and Ludwig, 2019). However, to the best of our knowledge, no such studies are conducted to review the present status of AI/ML applications in ASC management. The increasing amount of data captured by emerging technologies offer the ASCs new abilities to predict changes and identify opportunities (Kamble et al., 2020; Kamble et al., 2019a). The practitioners must be equipped with the latest knowledge to ensure that significant insights are derived from the collected data. Extensive testing and validation of emerging ML applications in ASC will be critical as agriculture is impacted by environmental factors that cannot be controlled, unlike other industries where risk is more comfortable to model and predict (Sennaar, 2019). Therefore, in this study, we present a systematic literature review (SLR) of 93 papers on ML applications in developing sustainable ASC. It is anticipated that the agricultural sector will continue to see the increasing adoption of ML in future and the results of this study will guide the researchers and practitioners to understand the present status of ML applications in ASC, which will help them to understand how adoption of ML will support the ASC to optimize farming practices to increase yields, crop quality and incomes in a sustainable manner.

The remaining of the paper is organized as follows: Section 2 presents a brief on sustainable ASC and ML algorithms. Section 3 presents the SLR methodology adopted in this study. Section 4 discusses the results of the SLR. An ML-ASC framework and implications based on the findings of the study are discussed in Section 5. The conclusions and limitations of the study are presented in Section 6.

2. Concepts used in the study

2.1. Agriculture supply chain

ASCs are like the fast-moving consumer goods (FMCG) supply chains in many ways but differ in terms of raw material procurement and the final product. The raw materials are procured from the fields, and the product is made for consumption by humans or animals. As seen in Fig. 1, the ASC includes several operations such as pre-production, production, storage, processing, retail, and distribution before the final product reaches the end consumers (Borodin et al., 2016).

A typical ASC includes multiple stakeholders such as farmers/producers, processors, certification agencies, traders, retailers, distributors, and final consumers. Therefore, the effective coordination of an ASC requires activities management, decision-making ranging from strategic, tactical, and operational levels (Patidar et al., 2018; Kamble et al., 2020). An ASC is complex in comparison with other supply chains due to the perishability of the product, high supply-demand fluctuations due to seasonality of the produce, and increasing consumer awareness towards produce provenance, quality, and safety (Kamble et al., 2020; M. Shukla and Jharkaria, 2013).

2.2. Challenges for ASC

Due to rapid industrialization and overpopulation, there is a fierce competition for natural resources, and the world is grappling with the challenge of feeding its people sustainably

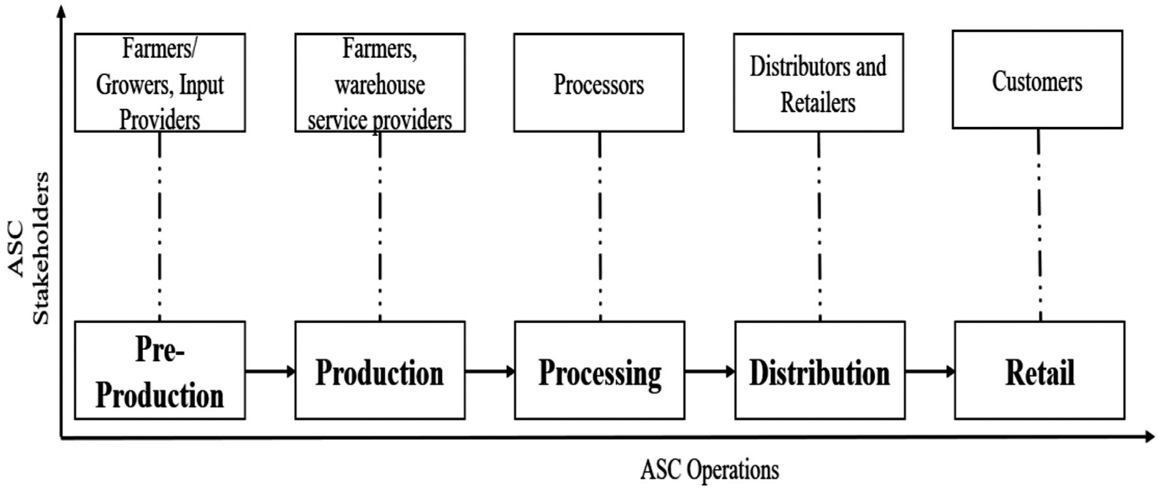

Fig. 1. ASC operations (Adapted from Borodin et al., 2016).

(Kummu et al., 2012; Pelletier and Tyedmers, 2010; FAO, 2009). It is estimated that the current food production systems and technologies will find it difficult to sustain the food demands of the next billion people (Elferink and Schierhorn, 2016). The critical issues that need to be addressed are lack of industrialization in the ASCs (Kamble et al., 2020), information asymmetry (Sharma and Parhi, 2017), inadequate management practices (Luthra et al., 2018), poor product traceability (Kamble et al., 2019a; Kamble et al., 2019b), and food safety and quality norms (Naik and Suresh, 2018). Moreover, with the recent advances in information and communication technology, a higher number of people are becoming aware and concerned about the triple bottom line aspects (social, economic, and environmental) of the ASCs. This has led to growing pressure from various stakeholders such as NGOs, consumer organizations, agro-based organizations, government institutions, and policymakers for developing sustainable food production and consumption strategies. Most of the practitioners and researchers agree to the fact that current ASCs need a drastic shift towards sustainability to comply with the United Nation's 2030 agenda of Sustainable Development Goals (SDGs) (Eyhorn et al., 2019).

2.3. Data-driven agriculture supply chains

In order to effectively cope up with the ever-increasing challenges of ASCs, we need a better understanding of the complex agricultural ecosystems (Kamilaris et al., 2017). This can happen by the usage of current disruptive technological platforms, which enable continuous monitoring of the physical agricultural environment (through wireless sensors) while producing endless amounts of data (Wolfert et al., 2017). Technologies such as the internet of services (IoS) and the internet of things (IoT) help in real-time sharing and collection of information through the help of connected devices (Kamble et al., 2019b). Ahumada and Villalobos (2009) report that enhanced information sharing, communication, coordination, and cooperation between the ASC nodes enabled by IoT platforms can augment sustainability in the ASCs. Wireless sensor technologies and IoT can reduce demand-supply gaps and address critical issues of food quality and safety (Zhong et al., 2017). As there is much data generated throughout the ASC, the analysis of this (big) data would enable farmers and organizations to draw valuable insights, thereby enhancing productivity through data-driven decision-making (Sharma et al., 2018). However, data-driven ASCs may pose challenges in terms of data storage, data collection, and data visualization. Other issues include data privacy, data security, data accuracy, and data access (Kamilaris et al., 2017; Sykuta, 2016). Moreover, a digital divide exists between developed and developing economies due to the lack of computational tools and adequate skillsets (Rodriguez et al., 2017).

Table 2
ML terminologies (adapted from Mohri et al., 2018).

Term	Definition
Example	Instances of data used for learning.
Feature	Set of attributes (or) vector associated with an example.
Hyperparameters	Parameters specified as inputs to the learning algorithm.
Hypothesis set	Set of functions used for mapping a set of features with the set of labels.
Label	Value(s) assigned to the examples.
Loss function	A function, measuring the difference between a true label and the predicted label.
Test sample	Examples used for evaluating the performance of a learning algorithm.
Training sample	Examples used for training a learning algorithm.
Validation sample	Examples used for tuning the parameters of a learning sample.

2.4. Machine learning algorithms

ML is defined as "the scientific study of algorithms and computational models on computers using experience for progressively improving the performance on a specific task or to make accurate forecasts" (Mohri et al., 2018). The term *"experience"* in the above definition refers to the historical data accessible to the learner for building a prediction model. These datasets can be digitized human-labeled datasets or data collected through interactions with the environment. Table 2 lists the common terminologies used in ML.

A general configuration of the ML system is presented in Fig. 2. Labeled or unlabeled training data is collected from different sources as input to the ML system. The knowledge base of the learning system decides the use of an appropriate ML algorithm, considering the decisions to be taken by the organization. Previous studies and datasets are also referred to validate the ML predictions obtained from the current datasets for quality output, improving the decision-making performance of the organization (Du and Sun, 2006).

The ML is categorized into three main tasks; supervised learning, unsupervised learning, and reinforcement learning. In

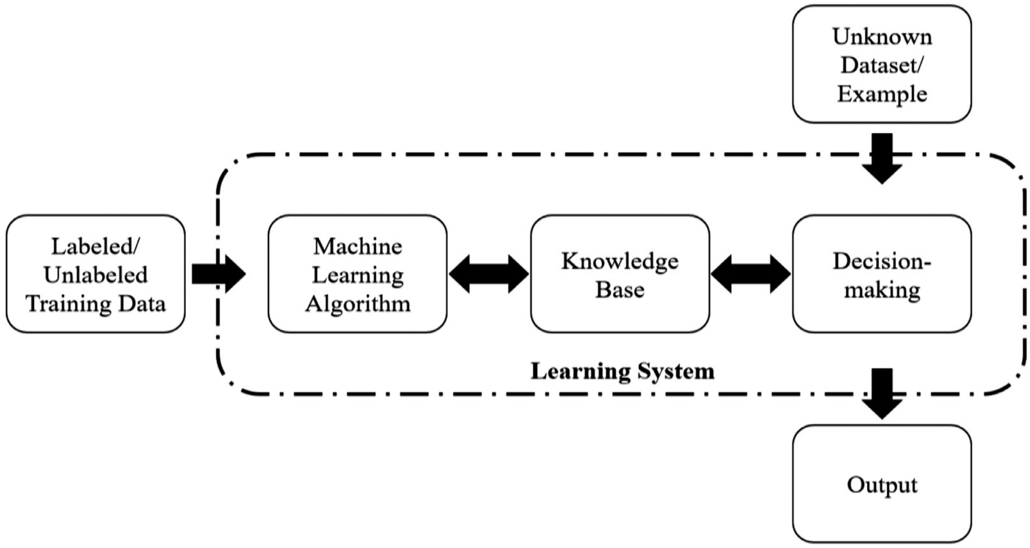

Fig. 2. A machine learning system configuration (adapted from Du and Sun, 2006).

supervised learning, a predictive model is developed using the labeled data with the prior knowledge of the input and the desired output variables. The goal of the supervised learning approach is to map the variables to the desired output variable (Zhu and Goldberg, 2009; Traore et al., 2017). Algorithms such as random forests, decision trees, Bayesian networks, and regression analysis are classified under supervised learning techniques. The unsupervised learning algorithms use unlabeled datasets without prior knowledge of the input and output variables. Unsupervised learning establishes the hidden patterns based on the unlabeled dataset and is primarily used for dimensionality reduction and exploratory data analysis (Jordan and Mitchell, 2015). Unsupervised learning includes algorithms such as Artificial Neural Networks (ANN), genetic algorithm, Instance-based learning models, deep learning, and clustering. In reinforcement learning, the training and testing datasets are combined, and the learner interacts with the environment to collect information. The learner gets awarded for his actions with the environment leading to an exploration versus exploitation dilemma. The learner must explore new unknown actions to gain more information as compared to exploiting the information already collected (Sutton and Barto, 2018; Mohri et al., 2018). Reinforcement learning algorithms are used for robot navigation, machine skill acquisition, and real-time decision-making. Reinforcement ML algorithms include Q-learning (SARSA max), Deep Q-learning (DQL), and Dataset Aggregation (dAgger).

A summary description of prominent ML algorithms is presented in Table 3.

Table 3
Description of ML Algorithms.

ML algorithm	Description
Bayesian network	A classification algorithm that predicts the output class based on Bayes' theorem by calculating class conditional probability and prior probability (Nielsen and Jensen, 2009).
Decision tree	This algorithm classifies the data into smaller subsets where each subset contains (mostly) responses of one class (either "yes" or "no") (Jordan and Mitchell, 2015; Mullainathan and Spiess, 2017).
Ensemble learning	This algorithm leverages the knowledge of the crowd, employing several independent models to make a prediction and aggregates the final prediction (Al-Jarrah et al., 2015; Liakos et al., 2018). Some of the prominent ensemble learning methods include random forests, gradient boosting machines (GBM), bootstrapped aggregation (bagging), AdaBoost, stacked generalization (blending), and gradient boosted regression trees (GBRT)
Regression Analysis	A classical predictive model that expresses the relationship between inputs and an output parameter in the form of an equation (Nasrabadi, 2007; Huang et al., 2012). Some of the commonly used regression models are linear regression, logistic regression, and polynomial regression.
Support Vector Machine (SVM)	A boundary detection algorithm that identifies/defines multidimensional boundaries separating data points belonging to different classes Vapnik (2013).
Artificial Neural Networks (ANN)	A computational and mathematical model inspired by the biological nervous system. The weights in the network learn to reduce the error between actual and prediction (Schmidhuber, 2015; Yang and Sudharshan, 2019). ANNs are further classified into perceptron networks, backpropagation networks, and Hopfield networks.
Clustering	Clustering algorithms such as k-means find k centroids by dividing the data into k clusters (Mohri et al., 2018).
Deep learning	Deep ANNs are referred to as Deep Learning because of multiple hidden layers (Salakhutdinov, 2015; Araque et al., 2017). The most common deep learning model is the convolutional neural network (CNN). These are further segregated into deep belief networks (DBNs), auto-encoders, and deep Boltzmann machine.
Genetic algorithm	Genetic algorithms are evolutionary computational and stochastic search algorithms that are often used in ML applications (Shapiro, 1999). Genetic algorithm is used in discrete spaces and find their applications where other gradient-based methods cannot be used. A genetic algorithm is best suited to situations where information is a critical criterion for performance.
Instance-based learning	This is a memory-based model that learns based on the comparison, i.e., examples are compared with instances from the training datasets (Azar and Dolatabad, 2019). Prominent algorithms in Instance-based learning includes learning vector quantization, k-nearest neighbor (KNN), and locally weighted learning (Liakos et al., 2018).

3. Review methodology

In this study, we utilized an SLR with a specific focus on reviewing the published research work systematically and attain an unbiased and objective summary of the current state and future potential of ML applications in ASC. SLR adopts an approach that is scientific and replicable (Cook et al. 1997) for evaluating and interpreting all the available research relevant to a question, topic, or phenomenon of interest (Booth et al. 2012). SLRs help in developing useful insights based on the theoretical synthesis of existing research and identifies possible gaps in literature (Tranfield et al. 2003; Kamble et al., 2018). We adopted the three-stage SLR methodology suggested by Tranfield et al. (2003), comprising of the pre-operational stage (“planning the review”), operational stage (“conducting the review), and post-operational stage (“review findings”).

3.1. Planning the review

The objective of our review was to study the applications of ML algorithms in ASC. The emphasis was to study the ML algorithms, as shown in Table 3, on the various ASC operations depicted in Fig. 1. More specifically, we sought to understand how the use of ML will help to make the ASCs efficient. To specify the conceptual boundaries, we used selected keywords covering ML algorithms such as decision trees, Bayes network, regression analysis, and artificial neural network. Not many limitations were applied to the keywords used for the “agriculture supply chain,” and the search included broad terms like “agriculture,” “food,” and “perishable items.” All the review papers were reviewed to match our review objectives and determine whether ASC was included in the scope of the papers.

3.2. Conducting the review

The keyword search was initially performed using the Scopus database. The Scopus database was selected as it encompasses a wide range of refereed journals belonging to major publishing houses such as Elsevier, Taylor and Francis, IEEE, Emerald, and Springer. Later the search was also extended to include ISI Web of Knowledge, Emerald Insights, and Business Source Premier so that we identify relevant work which is more comprehensive and not a sample of selected papers. However, to limit the number of papers for review, the conference contributions, articles published in trade journals, books, and book contributions were excluded from the search process. Backward and forward searches were conducted to ensure that the selected papers are comprehensive and significant studies in the field of ASC deploying ML algorithms are included. A total of 549 publications were found as an outcome of using the following keywords; "machine learning" OR "feature learning" OR "anomaly detection" OR "decision trees" OR" association rules" OR "Artificial neural networks" OR "Support vector machine" OR “Bayesian network” OR "genetic algorithm" AND "Agriculture" OR "Food" OR "Agri-food" OR "agricultural" OR "agri-business supply chain" OR “perishable supply chain.” The keyword search was implemented through a pairwise query taking into consideration one keyword from each category at a time. A review of the abstracts of these papers revealed that not all publications focused on ML applications in ASC. In some papers, ML and the other keywords were referred to in some other context. The following inclusion criteria were developed for the conducting the review: (1) The paper must have published in a peer-reviewed journal (2) The study focused on ML algorithms listed in Table 3. (3) The study discussed ML applications on any aspect of ASC management (4) Papers are written in English language (5) Should have passed the inter-rater reliability test. The papers were validated before the final selection was made for review. The papers were independently coded by three of the authors (two based in India and one from the UK), and their codes were compared for the difference in scoring to assess the inter-rater reliability (Armstrong et al., 1997). The papers with zero differences in the scores were included in the final review process whereas, the papers with differences went through the iteration process. The papers were selected for final review upon resolving the differences in the review score; otherwise, it was excluded from the review process. The validation process helped the authors to select quality papers matching to the objectives of the study instead of relying on the quality rating of the journal. The above selection criteria resulted in an exhaustive sample of 93 papers since it includes most of the published research in this area.

The publication selection process is outlined in Fig. 3.

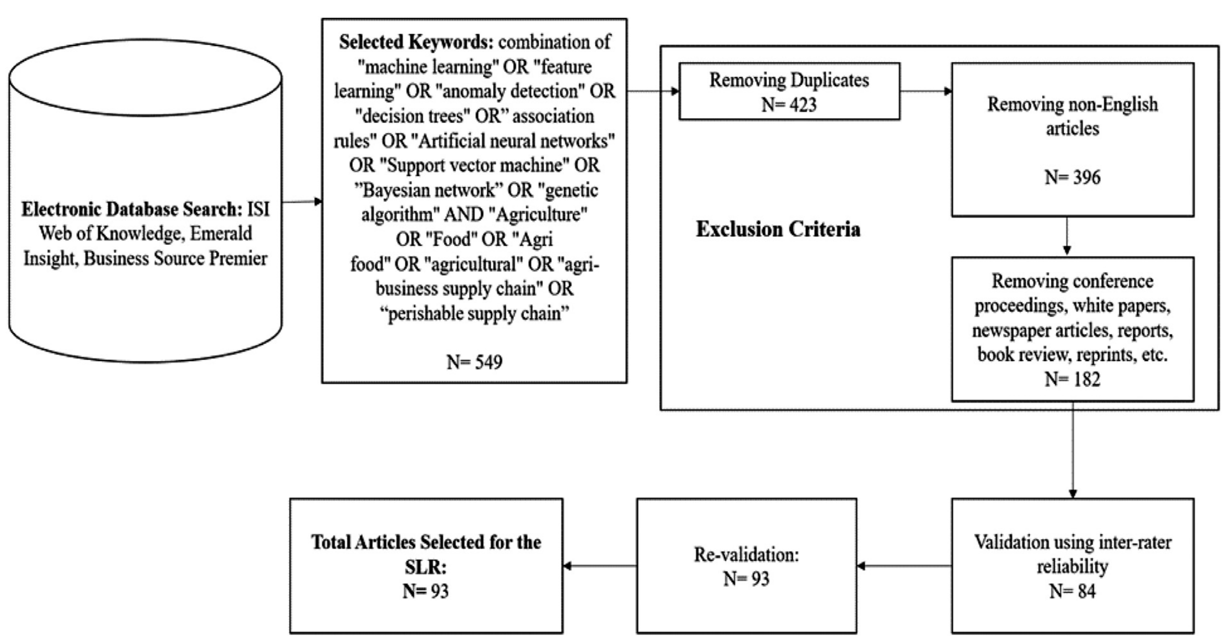

Fig. 3. Publication selection process.

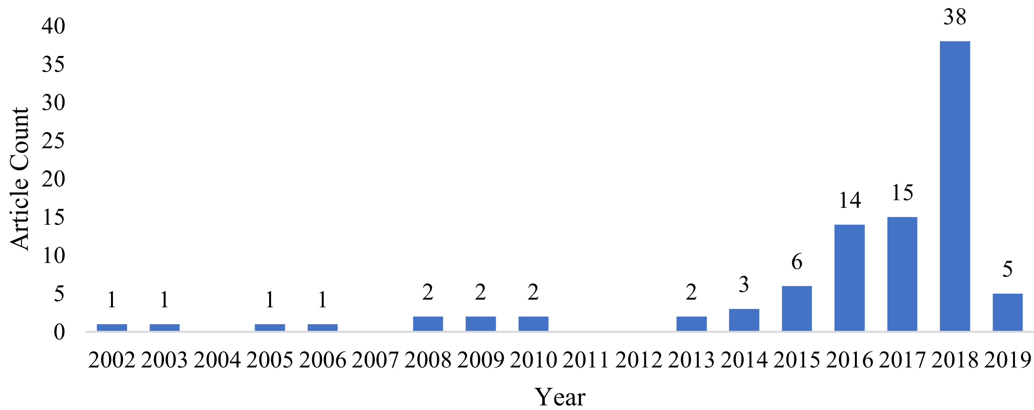

Fig. 4. Year-wise publications.

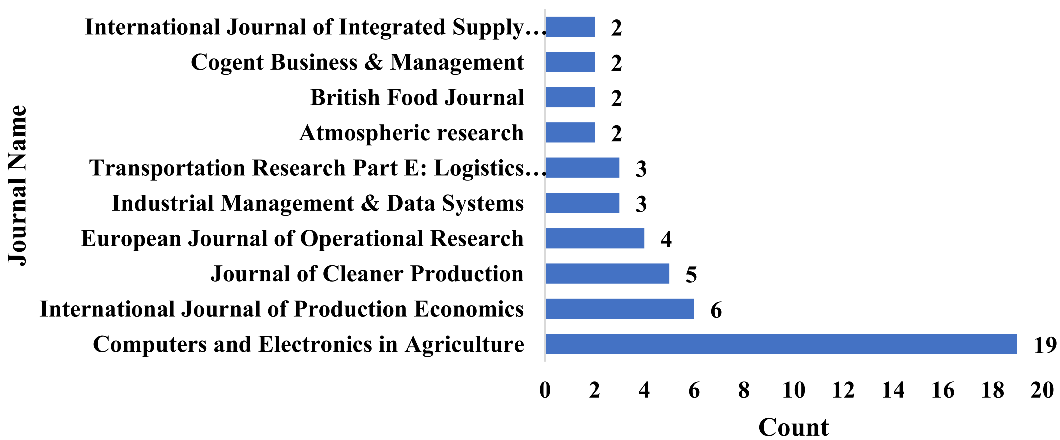

Fig. 5. Journal-wise publications.

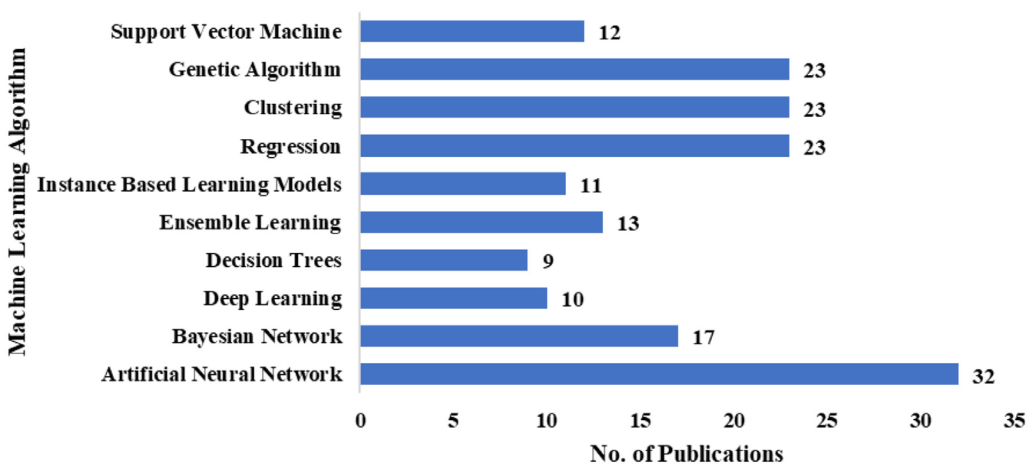

Fig. 6. Classification based on ML algorithm.

3.3. Descriptive statistics

The final sample contains 93 research papers. Studies on the topic of interest were available in or after 2002 with the pace of research picking up from 2015–16, showing increased interest by the researchers in applying ML algorithms to solve ASC challenges (see Fig. 4). It is also observed that high-quality peer-reviewed journals such as Computers and Electronics in Agriculture, International Journal of Production Economics, Journal of Cleaner Production, European Journal of Operations Research have recognized the need for research in this area (see Fig. 5). The use of different ML algorithms in ASC is presented in Fig. 6. It is observed that ANN is the most widely used ML algorithm (32 out of 93 studies), followed by regression, clustering, and genetic algorithm with 23 papers each. Few studies were found to use a combination of different ML algorithms. Fig. 7 represents the details of the ASC phases that have deployed the ML algorithms. The pre-production phase accounted for 39 papers, followed by a distribution phase with 29 papers, production (26 papers), harvest (17 papers), retailing (16 papers), and processing (5 papers). The statistics indicate

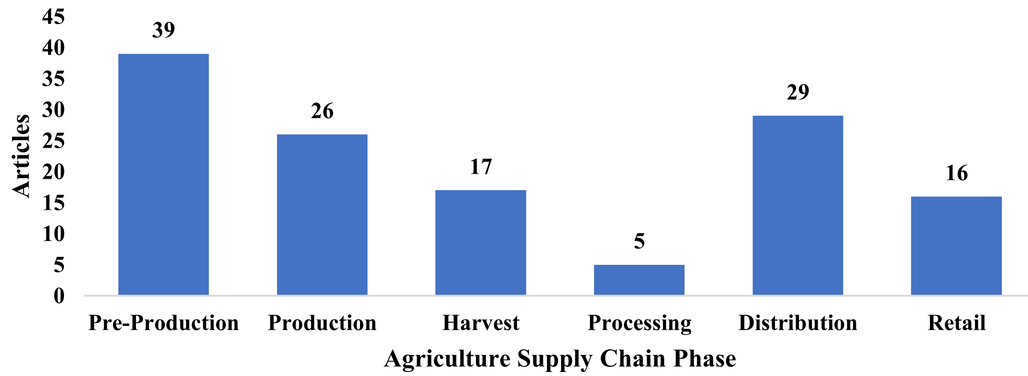

Fig. 7. Classification based on the agriculture supply chain phase.

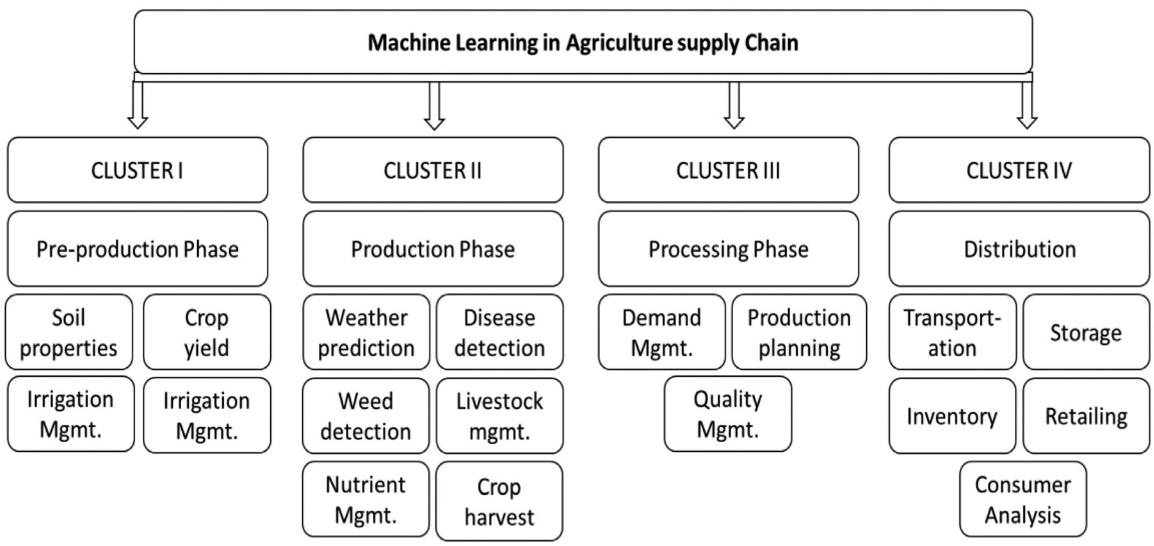

Fig. 8. SLR presentation framework.

that ML is mostly used in the pre-production phase for various applications such as predicting weather conditions, soil properties, weed detection, and disease classification.

4. Review findings and discussions

In this section, we analyze and present the findings of SLR in four clusters. These clusters represent the use of ML in the different ASC phases and include; pre-production, production, processing, and distribution (Aramyan et al., 2006; Ahumada and Villalobos, 2009). The use of ML in each cluster serves specific applications for improving ASC efficiency. It is observed from the SLR that ML is applied in the pre-production phase (Cluster 1) for the prediction of crop yield, soil properties, and irrigation requirements.

Similarly, ML is used for weather prediction, disease detection, weed detection, soil nutrient management, and livestock management during the production phase (Cluster II). In Cluster III (Processing Phase), the use of ML is for demand estimation and production planning. Inventory management and consumer analysis are the major application areas of ML in the distribution phase (Cluster IV). The SLR framework used for presenting the review findings is presented in Fig. 8.

4.1. Cluster I: pre-production phase

In an ASC, the pre-production forms the initial phase. The activities undertaken in this phase include crop yield prediction, prediction of soil properties, and irrigation (Chirinda et al. 2010). Accurate prediction of soil properties is essential because it helps in improving the soil management practices according to the land potential (Morellos et al., 2016). Hively et al. (2011) report that the prediction of soil properties leads to a better understanding of the soil ecosystem dynamics. Effective soil management practices lead to sustainable agricultural and environment management. In our study, 39 (42%) research papers dealt with the applications of ML in the pre-production phase. The ML applications in this phase include studies on developing a decision support system to predict product quality (Abbal et al., 2016), irrigation requirement in arid and semi-arid regions (Ali et al., 2018a, b) and improving the smart farming practices (Balducci et al., 2018).

4.1.1. Crop yield prediction

Crop yield prediction in agriculture is significant because it supports better crop management and plan marketing activities (Pantazi et al., 2016). As soon as the crop yield in a specific site is predicted, other farm inputs such as nutrients, fertilizers, and equipment requirements could be planned according to the soil and crop needs. Precision agriculture techniques make use of ML and signal processing techniques to aid decision-support in crop yield forecasting. Yield estimation and evaluation helped in coordination with harvest supply and enhanced the field efficiency (Ramos et al. 2017; Elavarasan et al., 2018). Table 4 presents a list of different ML algorithms used for crop yield prediction. ANN was

Table 4
ML algorithms in crop yield prediction.

ML Algorithm	Research Studies
ANN	Osman et al. (2015), Balducci et al. (2018), Chlingaryan et al. (2018), Crane-Droesch (2018), Elavarasan et al. (2018), Haghverdi et al. (2018), Khanal et al. (2018), Liakos et al. (2018), Mehra et al. (2018), and Saggi and Jain (2018)
Bayesian network	Zhang et al. (2017) and Elavarasan et al. (2018)
Clustering	Khanal et al. (2018), Liakos et al. (2018), and Elavarasan et al. (2018)
Deep learning	Osman et al. (2015), Crane-Droesch (2018), Liakos et al. (2018), Mehra et al. (2018), and Saggi and Jain (2018)
Decision tree	Liakos et al. (2018), Balducci et al. (2018), Elavarasan et al. (2018), Kouadio et al. (2018), and Chlingaryan et al. (2018)
Ensemble learning	Liakos et al. (2018), Kouadio et al. (2018), Khanal et al. (2018)
Instance-based learning	Liakos et al. (2018), Saggi and Jain (2018), Khanal et al. (2018)
Regression	Ridier et al. (2016), Liakos et al. (2018), and Elavarasan et al. (2018)
SVM	Khanal et al. (2018) and Liakos et al. (2018)

Table 5
ML algorithms for prediction of soil properties.

ML Algorithm	Research Studies
ANN	Tayyebi et al. (2017), Khanal et al. (2018), and Sirsat et al. (2018); Maiti et al. (2008)
Bayesian network	Sirsat et al. (2018)
Clustering	Khanal et al. (2018)
Deep learning	Khanal et al. (2018) and Sirsat et al. (2018)
Decision tree	Sirsat et al. (2018) and Kouadio et al. (2018)
Ensemble learning	Sirsat et al. (2018), Kouadio et al. (2018), and Prasad et al. (2018)
Instance-based learning	Sirsat et al. (2018)
Regression	Khanal et al. (2018), Sirsat et al. (2018), and Kouadio et al. (2018)
SVM	Khanal et al. (2018) and Sirsat et al. (2018)

found to be the most popular ML algorithm for crop yield prediction.

4.1.2. Predicting soil properties

ML in soil management is used for estimation of soil moisture content (Im et al., 2016; Prasad et al., 2018). In soil nutrient content, Morellos et al. (2016) applied two ML methods i.e., least squares support vector machines (LS-SVM), and Cubistin on the 140 wet soil samples. The findings of the study show that ML methods are not only capable of tackling non-linear problems but also outperformed in the prediction of all three soil properties studied. Nahvi et al. (2016) used the self adpative evolutionary (SaE) algorithm to enhance the performance of the extreme learning machine (ELM) architecture to estimate daily soil temperature. They then compared the performance of ELM and SaE-ELM models against genetic programming (GP) and artificial neural network (ANN) models developed in their study. Coopersmith et al. (2014) employed classification trees, k-nearest-neighbors, and boosted perceptron for soil dryness estimates and mentioned the k-nearest-neighbor and boosted perceptron algorithms both performed with 91–94% accuracy. A new method of ML named Crop Selection Method (CSM) was proposed by Kumar et al. (2015) to solve crop selection problems and maximize the net yield rate of the crop over the season which would help to improve net yield rate of crops. Accuracy in the prediction of soil conditions leads to efficient soil management practices. Table 5 provide list of some different ML algorithms used in learning soil properties.

Table 6
ML algorithms for irrigation management.

ML Algorithm	Research Studies
ANN	Raju et al. (2006), Kaneda et al. (2017), Navarro-Hellín et al. (2016), Liakos et al. (2018), Mehra et al. (2018), and Zhang et al. (2018)
Clustering	Liakos et al. (2018) and Goap et al. (2018)
Deep learning	Kaneda et al. (2017), Liakos et al. (2018), and Mehra et al. (2018)
Decision tree	Goldstein et al. (2018)
Ensemble learning	Goldstein et al. (2018) and Kaneda et al. (2017)
Instance-based learning	Liu et al. (2018)
Regression	Navarro-Hellín et al. (2016), Kaneda et al. (2017), Liakos et al. (2018), and Goap et al. (2018)
SVM	Liakos et al. (2018)

Table 7
ML algorithms for Weather Prediction.

ML Algorithm	Research Studies
ANN	Belayneh and Adamowski (2013), Crane-Droesch (2018), Mouatadid et al. (2018), Navarro-Hellín et al. (2016), and Saggi and Jain (2019)
Deep learning	Crane-Droesch (2018) and Saggi and Jain (2019)
Decision tree	Crane-Droesch (2018) and Saggi and Jain (2019)
Ensemble learning	Ali et al. (2018a), Ali et al. (2018b), and Saggi and Jain (2019)
Genetic algorithm	Wahyuni and Mahmudy (2017)
Instance-based learning	Saggi and Jain (2019)
Regression	Belayneh and Adamowski (2013), Cramer et al. (2017), Ali et al. (2018b), and Mouatadid et al. (2018)

4.1.3. Irrigation management

Irrigation management plays a critical role in affecting the quality and quantity of the crops. Irrigation scheduling and management cater to the spatial assessment of when, where, and how much to irrigate (Romero et al. 2018). An effective irrigation system makes use of soil moisture data, precipitation data, evaporation data, and weather forecasts for better decision-making (Goap et al., 2018). Efficient irrigation management in agricultural operations plays a vital role in maintaining the balance between climatological, hydrological, and the agronomical cycle for long term agricultural sustainability (Liakos et al., 2018). The ML algorithms used for developing efficient irrigation management systems are based on simulation and optimization techniques (Safavi and Esmikhani, 2013). The ML in irrigation management is used for estimation of evapotranspiration (Saggi and Jain, 2019; Torres et al., 2011), streamflows (Yaseen et al., 2016), and real-time management of reservoir release (Khalil et al., 2005). The different ML algorithms used for developing irrigation systems are listed in Table 6.

4.2. Production phase

ML is deployed in the production phase for weather prediction, weed detection, disease detection, livestock management, site-specific nutrient management, harvest, and crop quality management.

4.2.1. Weather prediction

Weather prediction plays a critical role in the crop production phase. The weather forecasts such as sunlight, rainfall, humidity, and moisture guide the optimal use of water for crop irrigation scheduling and planning (Trore et al. 2016; McNider et al. 2015). ML algorithms make use of both supervised and unsupervised methods for weather predictions (Bendre et al., 2016). Table 7 lists the different ML algorithms used for weather prediction.

Table 8
ML algorithms for disease detection.

ML Algorithm	Research Studies
ANN	Kamilaris and Prenafeta-Boldú (2018)
Clustering	Espejo-Garcia et al. (2018) and Singh et al. (2018)
Deep learning	Kamilaris and Prenafeta-Boldú (2018)
Ensemble learning	Kale and Sonavane (2018) and Su et al. (2018)
Instance-based learning	Kale and Sonavane (2018) and Pantazi et al. (2019)
Regression	Espejo-Garcia et al. (2018) and Singh et al. (2018)
SVM	Pantazi et al. (2019)

Table 9
ML algorithms for weeds detection.

ML Algorithm	Research Studies
ANN	Liakos et al. (2018)
Clustering	Mucherino et al. (2009) and Kale and Sonavane (2018)
Deep learning	Liakos et al. (2018)
Decision tree	Liakos et al. (2018)
EL	Liakos et al. (2018)
Instance-based learning	Liakos et al. (2018)
Regression	Mucherino et al. (2009)
SVM	Mucherino et al. (2009)

Table 10
ML algorithms for livestock management.

ML Algorithm	Research Studies
ANN	Vlontzos and Pardalos (2017) and Yazdanbakhsh et al. (2017)
Bayesian network	Liakos et al. (2018)
Clustering	Vlontzos and Pardalos (2017)
Deep learning	Pourmoayed et al. (2016)
Decision tree	Vlontzos and Pardalos (2017)
Instance-based learning	Vlontzos and Pardalos (2017) and Mucherino et al. (2009)
Regression	Yazdanbakhsh et al. (2017)

Table 11
ML algorithms for site-specific nutrient management.

ML algorithm	Research studies
ANN	Chlingaryan et al. (2018) and Sirsat et al. (2018)
Clustering	Chlingaryan et al. (2018)
Deep learning	Sirsat et al. (2018)
Decision tree	Chlingaryan et al. (2018) and Sirsat et al. (2018)
Ensemble learning	Chlingaryan et al. (2018) and Sirsat et al. (2018)
Instance-based learning	Sirsat et al. (2018)
Regression	Chlingaryan et al. (2018)

4.2.2. Crop protection

Effective crop protection measures include early identification and diagnosis of biotic stress factors (weeds and pathogens) and abiotic stress factors (nutrient, water deficiency) (Behmann et al., 2015). Precision agriculture technologies such as site-specific management have made it possible to detect pest infestations, diseases, and weeds before actual outbreaks (Lee et al. 2010). High density spatial and temporal information is required for effective site-specific management of plant diseases and weed detection. Many studies have proposed the use of automated disease detection platforms (based on pattern recognition and machine learning) for improving the accuracy and rapidity of the diagnosis results (Lu et al. 2017). The ML algorithms used for disease detection are listed in Table 8.

4.2.3. Weed detection

ML combined with machine vision is used for weeds removal, as weeds highlight distinct spectral reflectance that is considerably different from main crops (Strothmann et al., 2017; Jinglei et al., 2017; Bakhshipour and Jafari, 2018). Compared to manual methods, machine vision with pattern recognition algorithms and automatic classification techniques are more effective in monitoring crops (Zareiforoush et al., 2015) and weeds detection (Liakos et al., 2018; Kale and Sonavane 2018). ML algorithms use color, texture, and shape features in crops for object discriminations (Zhang et al., 2014; Tang et al., 2017), enabling automated solutions for weed detection and recognition (Binch and Fox, 2017). ML reduces the usage of weedicides and enhances agricultural sustainability. Table 9 lists different ML algorithms used for weeds detection.

4.2.4. Livestock management

Many studies (Liakos et al., 2018; Wang et al., 2018; (Lee et al. 2010) have highlighted usage of ML algorithms for effective livestock management such as grassland monitoring (Barrett et al. 2014), animal welfare (Pegorini et al. 2015), animal behavior tracking (Matthews et al. 2017), and livestock production (Craninx et al. 2008). Wathes et al. (2008) reported the use of ML algorithms for precision livestock farming, helping the farmers in evidence-based decision-making focused on real-time data monitoring and information systems (Berckmans and Guarino, 2017). Precision animal husbandry finds its importance in the domain of livestock management, health surveillance, livestock production, livestock welfare, and reducing environmental footprint (Morota et al., 2018). The studies on livestock management using ML algorithms are listed in Table 10.

4.2.5. Crop quality management

Crop quality management is essential as it helps in getting the right market price for the produce. Crop quality management practices such as site-specific nutrient management is an optimal approach for targeting homogenous crop/ field areas that require similar treatment (Chlingaryan et al., 2018). The most widely used ML algorithms for site-specific nutrient management are regression and clustering. In recent years, combinations of a crop model and global sets of gridded data have become vital tools in forecasting crop yields (Folberth et al. 2019). The following section presents more specific ML applications in the production phase of ASC presented.

4.2.6. Site-specific nutrient management

For sustainable land management practices, it is essential to improve the quality of soil and maintain adequate values of nutrients (Sirsat et al., 2018). The accurate detection and classification of crop quality parameters help in fetching a better price for the agricultural produce (Zhang et al., 2017). This also helps in reducing wastes and thereby minimizing the losses (Maione et al., 2016). Abbal et al. (2016) and Drury et al. (2017) suggests the use of Bayesian networks in enhancing crop quality management through effective decision-making. Table 11 lists the studies on site-specific nutrient management using ML algorithms.

4.2.7. Harvesting

Harvesting is the final horticultural procedure performed on the field after the ripening of the crops. The crop production estimates provide useful information to the cultivators for planning and allocating resources in the harvest and post-harvest activities (Ahn et al., 2018). The ML algorithms in this stage focus on predicting the crop yield using remote sensing data (Haghverdi et al., 2018). Kaudio et al. (2018) used an ensemble learning model for evaluating soil properties and compared it with random forests and logistic regression for predicting coffee yield in the harvest phase. Deep neural networks (Mehra et al., 2018) and data mining techniques such as k mean clustering, k nearest neighbor, ANN, and SVM (Mucherino et al., 2009) are used for accurate yield forecasts

Table 12
ML algorithms for demand prediction.

ML Algorithm	Author(s)
ANN	Borimnejad and Eshraghi Samani (2016) and da Veiga et al. (2016)
Genetic algorithm	Lin and Chen (2003), Madani et al. (2018), and Sitek et al. (2017)

Table 13
ML algorithms for production planning.

ML Algorithm	Research Studies
Bayesian network	Luangkesorn et al. (2016)
Clustering	Devapriya et al. (2017) and Khoshnevisan et al. (2015)
Genetic algorithm	Mousavi-Avval et al. (2017), and Nabavi-Pelesaraei et al. (2017)

during the harvest. SVM and machine vision is used for crop segmentation using foliage detection (Rico-Fernández et al., 2019). ML algorithms are used for predicting the change in the color of crops during the harvest stage (Sadgrove et al., 2018).

4.3. Processing phase

The main activities in this phase are demand prediction and production planning (for distribution) of the processed agricultural products. In the processing phase, the inedible raw materials are processed into more useful, palatable, and stable shelf forms for consumption (Augustin et al., 2016). Some of the prominent processing techniques are milling, heating, cooling, smoking, drying, and cooking (Weaver et al. 2014). Processing causes physical changes to the products and results in both detrimental and beneficial effects depending upon the processes used (Pellegrini and Fogliano, 2017). After the processing phase, the agricultural produce is packed and is ready for distribution and retail stages.

Modern food processing technologies deploy software algorithms based on ML. Chandrasekaran and Ranganathan (2017) suggest the use of a genetic algorithm in optimizing the CO_2 reduction during the processing of grains. Song et al. (2018) used Bayesian networks for minimizing food waste. Their study focused on waste processing and management for reducing the carbon footprint and mitigating climate change.

4.3.1. Demand prediction

A precise demand prediction of food requirements helps to avoid overstocking, overproduction, and overutilization of resources (Hofmann and Rutschmann, 2018). Table 12 lists the prominent ML algorithms used in demand prediction.

4.3.2. Production planning

The use of big data analytics in production planning helps in improving demand forecasting and production planning (Feng and Shanthikumar, 2018). ML algorithms help inefficient production planning through the reduction of setup time and better demand sensing (Lorena et al., 2011; Mehdizadeh et al., 2018). Table 13 lists the ML algorithms used for production planning.

4.4. Distribution phase

Distribution and retail phase connect food production and processing with final use and complete the farm to the fork loop (Manzini et al. 2019). In the distribution phase, the packaged agricultural product is sent to the distribution centers and warehouses.

Table 14
ML algorithms for distribution management.

ML Algorithm	Research Studies
Clustering	Ting et al. (2014), Devapriya et al. (2017), Hsiao et al. (2018), and Krisztin (2018)
Genetic algorithm	Qiang and Jiuping (2008), Larsen et al. (2010), Dolgui et al. (2018), Govindan et al. (2014), Nakandala et al. (2016), Madani et al. (2018), Buelvas Padilla et al. (2018), and Hsiao et al. (2018).
Regression	Ting et al. (2014), Saetta et al. (2015), and Krisztin (2018)

Most of the produce goes through a distribution channel before reaching the final consumer (Beaman and Johnson, 2006).

4.4.1. Transportation

The majority of the studies used genetic algorithm and focused on vehicle routing, minimizing the product damage, travel distance, and preserving the product quality (Qiang and Jiuping, 2008; Wang et al., 2018; Rabbani et al., 2016; Buelvas Padilla et al. 2018). The other studies in this phase used GA and memetic algorithms for handling integrated production and distribution scheduling problem (Devapriya et al., 2017) and association rule mining for identifying the storage location assignment problem based on the cloud for distribution and storage of perishable food products (Hui et al., 2016). ML algorithms are also used for estimating the freight (Krisztin, 2018), inventory management and payment delays (Kumar et al., 2016; M. Shukla and Jharkharia, 2013), estimation of product shelf life (Larsen et al., 2010), dynamic allocation (Lin and Chen, 2003; Piramuthu and Zhou, 2013), predicting supply chain risks under uncertainties (Luangkesorn et al., 2016). ML also finds its application in developing local food supply chains ensuring food safety and sustainability in the logistics network (Saetta et al., 2015). Table 14 lists the significant ML algorithms used in the distribution phase of the ASC.

4.4.2. Consumer analytics

ML techniques such as deep learning and ANN are used in the food retailing phase for predicting consumer demand, perception, and buying behavior (Ribeiro et al., 2018). Vlontzos and Pardalos (2017) highlight the application of ML techniques such as ANN, Decision tree, k-means type algorithms, genetic algorithm, nearest neighbor method, and rule induction in food retail with a focus on attracting customers attention. Singh et al. (2018) deployed a big data analytics-based approach of text mining (Jinbo et al., 2018) using SVM and hierarchical sampling with multi-scale bootstrap resampling for effective supply chain planning in retailing. Their study highlighted how decision-makers in the supply chain management could be informed about customer feedback based on sentiment analysis from social media platforms and help in developing a customer-centric retail supply chain. Maleki and Cruz-Machado (2015) highlighted the usage of Bayesian networks and ANNs for integrating customer-centric practices and customer values in food retail. Bayesian network was found to be useful in predicting the consumers buying behavior of different food products (Cene and Karaman, 2015; Chen et al., 2015; Borimnejad and Eshraghi Samani 2016; Fiore et al. (2017) and performing the quality checks of the retail food items (Santos-Fernández et al., 2017). Lilavanichakul et al. (2018) identified factors influencing consumers purchasing behavior for imported ready to eat foods based on ANNs and logistic regression techniques. Non-linear demand forecasting techniques were found to be more productive and accurate in forecasting the customer demand for different food products (da Veiga et al. 2016; Puchalsky et al., 2018). Table 15 lists the studies on customer analytics using ML algorithms.

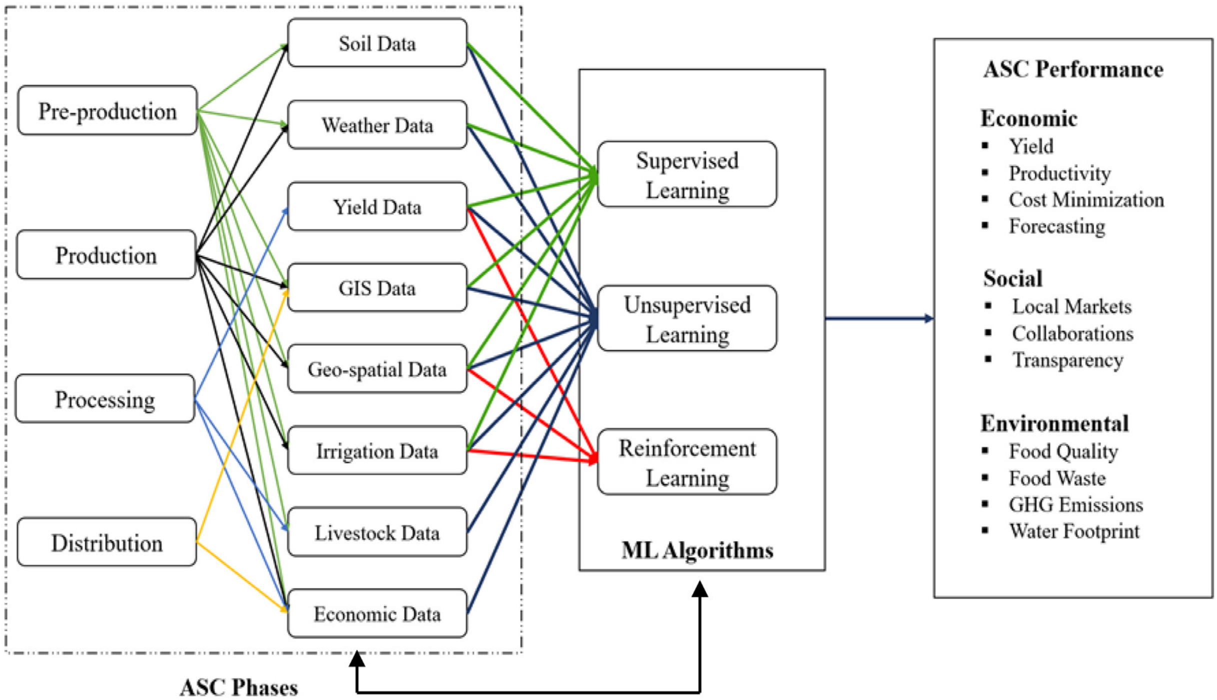

Fig. 9. A ML- ASC performance framework.

Table 15
ML algorithms for consumer analysis.

ML Algorithm	Research Studies
ANN	Lilavanichakul et al. (2018)
Bayesian network	Corney (2002), Cene and Karaman (2015), Maleki and Cruz-Machado (2015), Pourmoayed et al. (2016), Santos-Fernández et al. (2017), and Song et al. (2018)
Clustering	Corney (2002) and Chen et al. (2015)
Decision tree	Corney (2002)
Ensemble learning	Corney (2002)
Regression	Lilavanichakul et al. (2018)
SVM	Fiore et al. (2017)

Table 16
ML algorithms for inventory management.

ML Algorithm	Research Studies
Genetic algorithm	Dolgui et al. (2018), Hui et al. (2016), Kumar et al. (2016), Li et al. (2016), Piramuthu and Zhou (2013), Nakandala et al. (2016), Rabbani et al. (2016), Sazvar et al. (2016), and M. Shukla and Jharkharia (2013)

4.4.3. Inventory management

Inventory is an essential driver of cost as it utilizes storage space and ties up capital (Hofmann and Rutschmann, 2018). Maintaining limited stock or out of stock conditions lead to negative consequences such as reduced customer demand and loss in revenues. The availability of a product drives customer satisfaction and leads to profitability (Hanson et al., 2015). ML algorithms help in predicting daily demand and ensure that there are no inventory-related problems. Table 16 lists the ML algorithms used for inventory management in the ASCs.Table 16 lists the studies using Ml in ASC.

5. Proposed framework and implications

5.1. ML-ASC performance framework

The review findings indicate that ML has a vast potential for applications in the different ASC phases. The data generated from different sources in the ASC is used for making predictions and classification using different ML algorithms. The findings indicate that ML-driven technologies support improving the overall efficiency of ASC and address the various challenges faced by the industry, such as crop yield, soil health, and disease management. The potential benefits lead to an improvement in the ROI for all farms and minimize their losses. We use the findings from the literature to develop an ML-ASC performance application framework that can be used by the practitioners.

The proposed framework in Fig. 9 has three main components, the ASC phases, ML algorithms, and ASC performance.

5.1.1. ASC phase

The first component in this framework is represented by the different ASC phases that include pre-production, production, processing, and distribution. A considerable amount of data gets generated with the implementation of emerging technologies that need to be analyzed for gaining more in-depth insights. The study reveals that the data on soil, climate, yield, spatial, irrigation, etc., are analyzed using different ML algorithms for improved decision making. For example, it is observed that soil, weather, GIS, geospatial, irrigation, and livestock data are used for decision making in the pre-production stage. Likewise, these data are also used for decision-making in the production phase. The data generated in different phases of ASC is enhanced by specificity and situation awareness and is triggered by real-time events supporting agile field operations and includes intelligent assistance in implementation, maintenance and use of the technology. Our framework suggests that the focus of the ASC should be on implementing and using appropriate technology to generate the data. The literature has identified various technologies that promise huge potential in improving ASC performance. IoT platform combined with drone and sensor technologies is considered to be a promising data analytic technology for realizing high levels of operational control in the farms (Porter and Heppelmann, 2015). IoT is a powerful driver that can transform traditional farming practices into smart webs of connected objects that are context-sensitive and can be identified, sensed and controlled remotely. Drones have massive potential in effectively sensing and monitoring crops and livestock management. Sensors and actuators support a better understanding of the specific farming conditions that include weather and environmental conditions, livestock management, pest management, weed control, and disease detection in plants.

5.1.2. Machine learning algorithms

The second component in the framework is the ML algorithms that are used in different ASC phases. The study has found that supervised, unsupervised, and reinforcement learning techniques are used with specific objectives of improving ASC performance. Our framework suggests that the ASC phase and ML algorithms have a feedback loop that focuses on developing ML capability to extract maximum information from the data using appropriate ML algorithms. While it also suggests the best outcome from the ML-based analysis at different phases that would be used in ASC performance.

5.1.3. Sustainable ASC performance

The review findings reveal that the purpose of analyzing agriculture data using ML algorithms is to develop efficient ASCs. It was interesting to find that the ASC used ML not only to achieve economic benefits but also to achieve improved environmental and social performance. The discussions in Section 4 have identified the contribution of ML-enabled ASCs in achieving sustainable goals in different phases. In the pre-production phase, the ability to forecast timely rainfall using ML algorithms support to formulate effective water planning and resource management decisions (Ali et al., 2018a). The intelligent models can help in predicting accurate weather forecasts and thereby supports decision-making about flooding, crop sowing patterns, harvesting, and effective management of water resources (Terêncio et al. 2017). Efficient irrigation management enhances sustainable environmental performance and thereby enhances yield and productivity. Accurate predictions using ML algorithms are found to mitigate water-related disasters such as droughts and floods and reduce potential impacts on infrastructure and economy (Ali et al., 2018b). The literature in the production phase indicated that the site-specific and optimized nutrient management using ML algorithms ensure accurate crop yield and productivity (Chlingaryan et al., 2018). The use of remote sensing systems and ML algorithms have a positive impact on the yield production and nitrogen management while reducing operating costs and environmental impact. ML algorithms lead to the efficient management of resources and maximize technological investments by limiting and predicting hardware failures and replacements, reduce food losses, and optimize irrigation and sowing patterns (Balducci et al., 2018). In the processing phase, ML algorithms are used for reduced GHG emissions, improving environmental quality (Chandrasekaran and Ranganathan, 2017; Nabavi-Pelesaraei et al., 2016; Mousavi-Avval et al., 2017). Improved environmental quality reduces poverty, enhances economic growth while improving people's health (Bhateja et al., 2011). The reduced post-harvest losses (PHL) by using appropriate ML algorithms reduce environmental damage, enhance food safety, and thereby enhance social sustainability through active local market development by meeting customer and market demands (Syahruddin and Kalchschmidt, 2011). Murthy et al. (2007) indicated that if the PHL losses are minimized, the prices of agricultural commodities will reduce drastically. In the distribution phase, the use of ML has resulted in improved social and economic sustainable performance through enhanced food safety, quality, economic savings, and customer satisfaction (Buelvas Padilla et al., 2018; Govindan et al., 2014). The use of ANNs in demand forecasting leading to economic savings and enhanced customer satisfaction (de Vaiga et al., 2016). Similarly, the optimized vehicle routing and fleet management contribute to fuel savings enhancing environmental and economic performance in last-mile delivery (Wang et al., 2018; Dolgui et al., 2018; Hsiao et al., 2018; Hui et al., 2016).

The above discussions drive us to include sustainable ASC performance as the third significant component of the proposed ML-ASC performance framework. The sustainable ASC is proposed to address the three dimensions of sustainability, namely: Economical, Social, and Environmental (Elkington, 1998).

5.2. Implications of the study

5.2.1. Implications for practitioners

The congregating need for a transparent, efficient, and sustainable supply chain is driving the digital transformation in ASC. The practitioners are therefore required to assess their present position, while the emerging technologies are disrupting their industry. The study reveals enormous benefits to the ASC that have developed the ML capability implying that the adoption of ML in decision making is a must. With the increasing demand for food and decreasing interest of farmers in agriculture occupation, there is a need for a massive increase in farm productivity fulfilling the ecological and social requirements. The review suggests that the ML applications can be extended to different phases of ASC to create an intelligent web of interoperable entities, which will help to control and monitor all the agricultural processes. The analysis of data collected from sensors (Kale and Sonavane, 2018; Goap et al., 2018; Liakos et al., 2018) and drones (Fernández et al., 2018; Rehman et al., 2019; Rico-Fernández et al., 2019) deliver insights that enhances farm productivity and farmers profitability. It is, therefore, evident that the practitioners will have to plan new investments in emerging technologies to solve the social and environmental problems, simultaneously increasing efficiency. Apart from the sustainability benefits, the ML applications also contribute to improving supply chain visibility, transparency, and product traceability. However, this will require the practitioners to explore the possibilities of integrating different sources of ML data with blockchain technology and other technologies (Tian, 2016; Sharma et al., 2018, Kamble et al., 2018).

The ML algorithms can be used for improved product distribution by predicting the delays in outbound and inbound shipments, optimized vehicle routing, and improved fleet management. The use of ML will ensure real-time tracking of products enabling product traceability, monitoring the food safety norms, and quick response product recalls in case of contamination or identification of fake products. For the practitioners in the processing phase, the ML applications hold tremendous potential for transforming the production systems into data-driven smart manufacturing systems. The IoT and cyber-physical systems will transform the manufacturing processes into autonomously connected objects with embedded intelligence. The ML algorithms increase the likelihood of early detection of food safety-related issues. ML algorithms based on simulation technologies are found to support early mitigation of risks in ASCs. It is therefore implied that the practitioners should invest in sensor technologies for monitoring the real-time processing activities, ensuring machine interoperability, and real-time decision making.

The review finds that the ML algorithms have contributed to developing new servitization models to serve the customers efficiently (Helo et al. 2017). The practitioners will be required to deploy IoT and other smart devices for providing data access to the customers, as well as capturing data from them. This will provide customers with the ability to trace the products back to their origin, enhancing their experience. The information on customer buying behavior will help the practitioners to predict the customer preferences and needs improving their product development performance. The practitioners can use ML for predicting the demand based on previous buying patterns. This, in turn, will also improve their supplier relationships, reducing the supplier-related delays and inventory forecast accuracy. ML algorithms will facilitate the optimal usage and utilization of resources throughout the ASC, ushering a new dimension of symbiosis in this sector. Collaboration between various ASC organizations will accelerate effective waste management and disposal solutions. The machine vision applications combined with ML algorithms can be beneficial in predicting plant stress conditions, which will help in taking proactive decisions on the target plants without harming other plants in the vicinity. This will help in the optimal use of resources such as fertilizers, water, pesticides, and weedicides.

Despite the benefits associated with the use of ML in ASCs, the practitioners will be required to address a few challenges (technical and non-technical) for the successful adoption of ML. Overcoming these challenges will accelerate new technological developments and value creation for the stakeholders. Most predominant technical challenges that need to be addressed by the practitioners include the following;

- *Data security*: Issues related to data access, data storage, data ownership, and use of data.
- *Infrastructure*: In developing economies, internet connectivity is a significant barrier preventing technology adoption and penetration. The deployment of smart devices will involve significant investments and time before connectivity issues are resolved.
- *Standardization of data*: The data gets generated from different ASC phases leading to the issues related to data standardization. This will require to have a robust sensor network and effective data conversion and standardization techniques.
- *Device interoperability*: Device interoperability will be a significant technical barrier that would be needed to overcome for ensuring the penetration of ML techniques.

The non-technical barriers include lack of policy regulations on the use of data, the involvement of different stakeholders, and information sharing practices. Further, there is a shortage of human resources with analytical skills that may affect the adoption of ML applications. Therefore, it is required to develop capacity building programs for enhancing the skill set of the farmers and other stakeholders in the ASCs.

5.2.2. Implications for researchers

Based on the discussions in this study, we present the following broad areas needing further investigation from researchers.

i. The study focuses on ML applications in analyzing the data, and less attention is paid on how the data from different innovative technologies is captured, stored, analyzed, and shared across the different phases in ASC. More research is required in this direction.
ii. The findings indicate that ML helps to enhance ASC visibility. However, it would be interesting to know the impact of such influence. The future studies should aim at measuring the impact of ML on ASC and provide specific guidelines on how the ASCs should deploy ML for enhanced supply chain visibility. The ML-ASC performance framework proposed in the study may be used as a guiding framework for such studies.
iii. The future studies should focus on how ML can transform the existing production systems into data-driven smart manufacturing systems?
iv. The future studies should aim at developing focused customer frameworks, which should capture insights on customer buying behavior.
v. More studies on how ML algorithms can contribute towards facilitating the optimal use and utilization of resources throughout the ASC is required to be conducted.
vi. Studies on identifying the relationships between the various barriers for implementing ML in ASCs are required. The identification of the driving and dependence barriers will help in expediting the ML implementation.
vii. Future studies may focus on comparing the performance of different ML algorithms. For example, a comparative study to test the performance of regression analysis and ANN may be performed in predicting the moisture content in the soil.

5.2.3. Implications for policymakers

There is a lot of expectations from the local government by the ASC members. Considering the high cost of investment in digital technologies and developing ML capabilities, the policymakers are expected to subsidize investments in digital technologies and make it more affordable so that it can be used widely. In the emerging markets, there exists a considerable gap between the available resources and education. Many farmers do not have access to the internet, mobile phones and training on the new technologies and data interpretation. Advisories are required to be developed to assist the farmers in understanding the information and recommend suitable mechanisms to improve farm productivity. It is therefore implied that the policymakers should plan to connect the farmers in the rural areas and work with governments and technology companies for pulling costs of data collection equipment and software. There is also the need to provide extensive and advanced education, which revolves around utilizing these farming measures globally.

6. Summary

The present study is based on an SLR to investigate the current state of research on machine learning (ML) applications in ASC. The SLR was performed on 93 research articles, which were categorized using different ML algorithms across different ASC phases. The study finds that all three ML algorithms, that is, supervised, unsupervised, and reinforcement learning is used to develop sustainable ASCs. The main contribution of the study is the ML-ASC performance application framework (as shown in Fig. 9) that will further guide academics and practitioners to understand the current state of literature in this field. The study reveals considerable benefits to the ASC that have developed the ML capability, implying that the adoption of ML in decision making is beneficial. Considering the high cost of investment in digital technologies and developing ML capabilities, the policymakers are expected to subsidize investments in digital technologies and make it more affordable so that it can be used widely.

As with any research, our study also has few limitations. ISI Web of Science was used as the database for searching the papers for conducting the SLR. We might likely have missed a few important research papers that are not included in the ISI Web of Science database. The SLR covers a timeframe of 19 years, i.e., 2000–2019. The list of research studies selected is comprehensive as they are selected from refereed journals, although not exhaustive. Future studies can therefore include other databases beyond ISI Web of Science. The framework presented in this study is based on the findings from the review of literturature which has not been tested empirically. Hence future studies may be conducted to validate this framework empirically. Moreover, future studies can also explore the extent of the ML application to ASCs in different regions across the world and provide a comparative assessment.

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