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MACHINE LEARNING ALGORITHMS IN AGRICULTURE: A LITERATURE REVIEW ON CLIMATE AND PRICE PREDICTION, PEST AND DISEASE DETECTION, AND PRODUCTION MONITORING

ALGORITMOS DE APRENDIZADO DE MÁQUINA NA AGRICULTURA: UMA REVISÃO DA LITERATURA SOBRE PREVISÃO CLIMÁTICA E DE PREÇOS, DETECÇÃO DE PRAGAS E DOENÇAS E MONITORAMENTO DE PRODUÇÃO

ALGORITMOS DE APRENDIZAJE AUTOMÁTICO EN LA AGRICULTURA: UNA REVISIÓN DE LA LITERATURA SOBRE PREDICCIÓN CLIMÁTICA Y DE PRECIOS, DETECCIÓN DE PLAGAS Y ENFERMEDADES Y MONITOREO DE PRODUCCIÓN

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ABSTRACT

The growing demand for food necessitates the application of advanced technologies in agriculture. Furthermore, due to food production, pests, and climate change incidents are a real-time challenge for farmers. Due to the growing need to apply algorithms in the field, we investigate the algorithms most cited, used, and ongoing projects in the last three years, from 2019 to 2021 Therefore, we evaluated articles that focus on supervised and unsupervised algorithms. This literature review presents an overview of algorithms usage in agriculture. A total of 81 articles were analysed. Our contributions as

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a) an analysis of the state-of-the-art on applying algorithms to various agricultural functions and b) a taxonomy to help researchers, governments, and farmers choose these algorithms. The literature review systematization methodologically summarizes the following: the definition of research objectives and questions, the definition of criteria, search strategies, screening of results, synthesis, and analysis of data, discussion, review, and conclusions. This article adds discoveries about the application of algorithms in crops, machinery, and processes and points out new lines of research.

KEYWORDS: Algorithm. Agriculture. Random Forest. Machine Learning. Drought. Forecast. AI.

RESUMO
A crescente demanda por alimentos exige a aplicação de tecnologias avançadas na agricultura. Além disso, devido à produção de alimentos, as pragas e os incidentes de mudanças climáticas são um desafio em tempo real para os agricultores. Devido à crescente necessidade de aplicação de algoritmos no campo, investigamos os algoritmos mais citados, utilizados e projetos em andamento nos últimos três anos, de 2019 a 2021 Portanto, avaliamos artigos que enfocam algoritmos supervisionados e não supervisionados. Esta revisão da literatura apresenta uma visão geral do uso de algoritmos na agricultura. Foram analisados 81 artigos. Nossas contribuições são a) uma análise do estado da arte na aplicação de algoritmos a várias funções agrícolas e b) uma taxonomia para ajudar pesquisadores, governos e agricultores a escolher esses algoritmos. A sistematização da revisão de literatura sintetiza metodologicamente: a definição dos objetivos e questões da pesquisa, a definição de critérios, estratégias de busca, triagem de resultados, síntese e análise dos dados, discussão, revisão e conclusões. Este artigo acrescenta descobertas sobre a aplicação de algoritmos em culturas, máquinas e processos e aponta novas linhas de pesquisa.

PALAVRAS-CHAVE: Algoritmo. Agricultura. Floresta aleatória. Aprendizado de máquina. Seca. Previsão. IA.

RESUMEN
La demanda de alimentos está creciendo cada año y exige aplicaciones tecnológicas más significativas en el campo. Además, debido a la producción de alimentos, las plagas y los incidentes relacionados con el cambio climático representan un desafío en tiempo real para los agricultores. Ante la creciente necesidad de aplicar algoritmos en el campo, investigamos los algoritmos más citados, utilizados y proyectos en curso en los últimos tres años, de 2019 a 2021. Por lo tanto, evaluamos artículos cuyo enfoque principal fue en algoritmos de aprendizaje supervisado. Esta revisión de literatura presenta una visión general del uso de algoritmos en la agricultura. Se analizaron un total de 81 artículos. Nuestras contribuciones incluyen: a) un análisis del estado del arte en la aplicación de algoritmos a diversas funciones agrícolas y b) una taxonomía para ayudar a investigadores, gobiernos y agricultores a elegir estos algoritmos. Este artículo aporta descubrimientos sobre la aplicación de algoritmos en cultivos, maquinaria y procesos, además de señalar nuevas líneas de investigación.

PALABRAS CLAVE: Algoritmo. Agricultura. Bosque aleatorio. Aprendizaje automático. Sequía. Previsión. IA.

1. INTRODUCTION

Agriculture is essential for developing cultures that, in addition to feeding the nation, are the base for exportation from several third world countries. In many of these countries, agriculture represents a large share of the resources coming from exports to the national economy (Wang *et al.* 2019). Due to the importance of agriculture for the local and export economy, several technologies are used to maintain, and control products such as the use of drones (Chinnaiyan; Balachandar, 2020), IoT (Garg *et al.,* 2021), satellite imagery (Moumni; Lahrouni 2021) and mostly machine learning.

The primary needs of farmers have continued to be problematic addressed in various corners of the world for a long time, such as combating various types of pests (fungi, bacteria, insects, and rodents); water resources management trying to maintain the water supply and avoid drought; knowledge the players in the production chain and maintain trusting relationships within this supply chain; predict climate changes that affect crops and crops; price forecasting is a problem that affects futures contracts for the sale of grains.

Problems such as droughts, pests, uncertainties about price determination, the need for planning and monitoring, the use of technologies are addressed as some challenges for agriculture, and the relationship of algorithms in the treatment of these issues. Figure 1. There is a gap on identifying how machine learning is being used in the last years, this literature review focuses on this time window. This work presents contributions that serve for future research; we highlight current research on machine learning, present a simplified taxonomy of the application of machine learning in agriculture, and indicate future opportunities and challenges in this area.

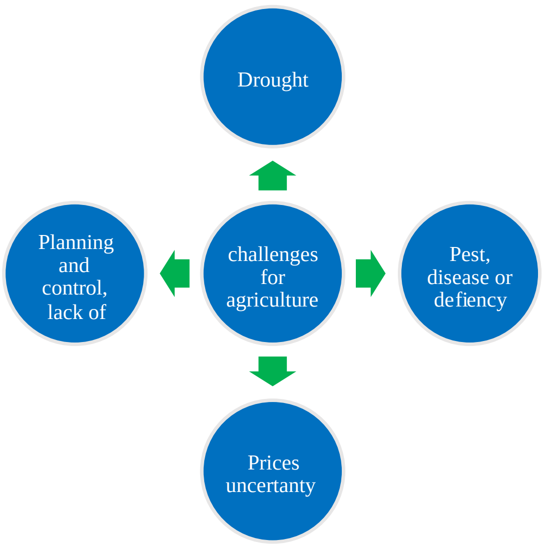

Figure 1. Challenges for agriculture

The text is organized as follows: Section 2 presents the materials and methods and research questions; section 3 presents the results obtained from the selected articles; section 4 presents the limitations; section 5 presents the challenges in the area with open questions; we end in section 6 with our conclusions and indications for future work.

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2. MATERIALS AND METHODS

The current study is a systematic literature review designed to provide a broad view of the application of machine learning algorithms in agriculture. The Biolchini *et al.,* (2005) and Budgen and Brereton (2006) methodology was followed to outline a plan for this systematic literature review. This review was carried out following these steps: Planning; development of research questions; description of information sources and operationalization of data collection; description add from data sources; description of choice criteria; description of quality control and refinement criteria; comparison of filter results against search questions.

2.1. Planning

A protocol was developed that included: search sources, filtering criteria, and comparisons between filter results and search questions related to the application of algorithms in agriculture. This literature review attempted to identify unique studies after applying inclusion and exclusion criteria. These were summarized in the results. One author developed the filtering process, applied criteria, and research questions; other authors reviewed the research questions and carried out reviews. Online electronic databases were used for the searches (cited below in the section: Information sources).

2.2. Research questions

The questions for the survey were defined as they are important to define the direction of the review process. With the questions, the authors intend to identify cutting-edge and innovative research that focuses on the application of machine learning algorithms in agriculture; We also aim to identify new trends, challenges, and solutions with the questions. The Table 1 describes the questions.

Table 1. Research questions

Id	Question
RQ1	Which studies use algorithms for forecasting whether or drought?
RQ2	What algorithms are used for pest, disease, or deficiency detection?
RQ3	What algorithms are used for price prediction?
RQ4	What algorithms are used in planning, controlling, monitoring agricultural production?
RQ5	What technologies are used in conjunction with machine learning?
RQ6	Is it possible to elaborate on a basic taxonomy?
RQ7	What other bibliometric data can be obtained?

2.3. Information sources

Online electronic databases were selected that allow a broad search in the current literature to collect a more significant number of articles. Online electronic databases were: ACM, Hindawai, IEEE, MDPI, Microsoft Academic, PlosOne, ScienceDirect, Springer, Taylor and Francis Online.

2.4. Inclusion and exclusions criteria

After all, studies were obtained, the inclusion and exclusion process were started. This process is a filter on the obtained jobs. The most relevant articles relating to the topic were selected by using the criteria. Also removed are conference names correlated with the search strings due to the particularities of each electronic database. Articles are separated by titles and abstracts and then grouped. In this grouping, duplicate articles based on title are removed, and later we removed the duplication based on authors, as some works repeatedly appear in more than one database. The article’s overview approach is carried out to detect particularities in the text as specific technologies and algorithms. The number of articles removed is significant due to the difficulty of distinguishing between the application of statistical methods, other surveys, or very small abstracts that still appear; non-aligned articles are removed. Only articles in English were selected from 2019 to 2021. The period chosen between 2019 and 2021 is important because it addresses the pre-pandemic and alternatives without the influence of LLM (large language model) algorithms as launched such as ChapGPT launched in 2022, in this way this article is a time frame allowing comparability of the algorithms used before this period, in addition to not having identified previous similar reviews, and thus created the possibility of post comparison of prompt-based tools and reanalysis of these other algorithms. The criteria are in Table 2.

Table 2. Inclusion and exclusion criteria

Id	Inclusion criteria
IC1	Articles in English
IC2	Publication period: 2019 to 2021
IC3	Articles containing the search strings in the title
Id	Exclusion criteria
EC1	Articles older than 3 years
EC2	Complete books
EC3	Language other than English
EC4	Theses, dissertations
EC5	Duplicate publications

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EC6	Commercial materials or white paper
EC7	Publication with less than 4 pages
EC8	Articles with anonymous authors
EC9	Literature reviews or surveys
EC10	Corrections or errata
EC11	Academic monographs
EC12	Regulations and policies

2.5. Quality assessment

We adopt some quality criteria during the screening selection process that are important for the general analysis of the collected works. Among them, we cite contextualization of work with current problems, citation of technologies of interest to this search, if the article presents a machine learning application to solve problems if the article presents future work or indicates directions for future improvements.

3. RESULTS

The results are presented in the following section. The answers to the questions are presented with the help of the general interpretation of the selected works. The applied article selection process found 6,030 articles, of which, after passing through the filter funnel, resulted in 88 articles used. Articles were grouped according to the publisher: ACM 5, arXiv 2, BASE 2, Hindawi 3, IEEE 11, MDPI 26, Microsoft Academic 4, PlosOne 2, ScienceDirect 31, Springer 1, Tandfonline 2.

Figure 2 show publications grouped by year (according to the inclusion criteria).

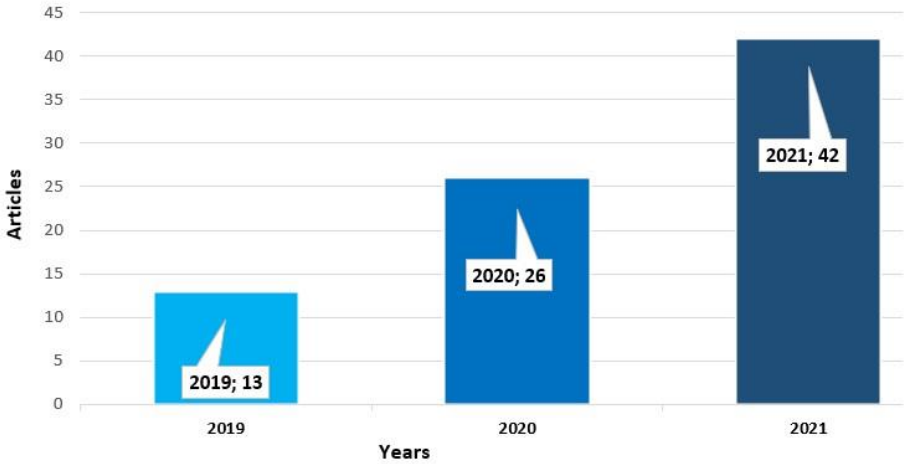

Figure 2. Publications per year

3.1. RQ1 - Which studies use algorithms for forecasting whether or drought?

The work of Ketchum *et al.,* (2020) developed a land classifier using a geospatial database and LandSat satellite images to detect irrigated areas; the one classified used was the random forest (RF) identifying areas with decreased irrigation and others with increase. The work of Xavier *et al.* (2020) used machine learning (especially the algorithms: (RF) and decision trees (DT) to understand the occurrence of drought in northeastern Brazil, the characterization of drought used the standard precipitation index, among other data; the use of RF and DT allowed farmers to adopt and adapt strategies for water management, especially in water deficit scenarios; In time series analysis there is data delay. Thus, the use of other non-linear techniques were applied.

Muniasamy (2020) They developed a study indicating the applicability of IoT and machine learning in data collection, processing, and decision making in intelligent agriculture, citing the use of robots to monitor plants and pests; cites the use of drones to monitor soil and crops and analytics to predict events based on historical data on temperature, humidity, wind speed, and others. A proposal for a machine learning approach to rainfall forecast, using several attributes such as humidity and temperature applying the algorithms multiple linear regressions (MLR), K nearest neighbor (KNN), support vector machines (SVM), RF; of which the RF had the best accuracy, Premachandra (2021).

Six machine learning models classification and regression trees (CART), boosted regression trees (BRT), random forest (RF), multivariate adaptive regression splines(MARS), flexible discriminant analysis(FDA), and SVM) were used to map drought risks in Australia from 1994 to 2013; producing a risk map that allows the planning of water resources and contingency, Rahmati *et al*., (2019) Rahmati *et al.,* (2020). Moumni and Lahrouni (2021) carried out identification of types of crops based on classified images via machine learning, using SVM and artificial neural network (ANN), images from the Sentinel-1 and Sentinel-2 satellites showing the soil mapping; demonstrated that applications of these classifiers increase when working with images.

Prodhan *et al.* (2021) aimed to identify and pinpoint the magnitude and duration of future drought occurrences using data from pre-existing designs applied to RF and gradient boosted models (GB). Gong *et al.* (2021) used evapotranspiration data with machine learning algorithms (particle swarm optimization (PSO), genetic algorithm (GA), and extreme learning regression (ELR) to estimate the amount of water during the crop irrigation process. Li *et al.* (2021) develop a disaster vulnerability model for drought risks; also aiming to predict crop yields and insurance rates; to assist in agronomic management, they used satellite images and machine learning, used various data such as precipitation, leaf area, and others; the machine learning algorithms used were RF and multi linear regression (MLR).

Dubois *et al.* (2021) modeling of the irrigation problem was carried out so that predictions could be made, including soil and potato crop data; ANN, RF, and SVM were used; were successful in predicting water values. Feyisa *et al.* (2020) applied time series of vegetation indices data obtained from the Moderate Resolution Imaging Spectrometer (MODIS) with machine learning algorithms

(SVM, RF, and C5.0 (C5 algorithm)) to perform irrigation and rainfall patterns. Yamac¸ and Todorovic (2020) carried out a study on the evapotranspiration of potato plantations using machine learning algorithms (KNN, ANN and adaptive boosting (Adaboost)), indicate the K nearest neighbor (KNN) when meteorological data is limited, in other situations they recommend the use of ANN.

Folberth *et al.* (2019) applied gradient boost and RF to predict the output of models with a low and acceptable spatial-temporal resolution for the corn crop, indicating development potential by applying machine learning in the development of crop model emulators. The articles mentioned above are summarized in Table 3 with data on authors, year, country of the first author, number of citations and main algorithm mentioned in the body of the article; articles related to Research Question 1.

Table 3. Authors, year, electronic database, citations, algorithm

Author	Year	Database	Country	Citations	Algorithm
[Ketchum et al. 2020]	2020	MDPI	USA	6	RF
[Xavier et al. 2020]	2020	MDPI	Brazil	3	RF, DT
[Muniasamy 2020]	2020	IEEE	Saudi Arabia		not specified
[Premachandra and Kumara 2021]	2021	IEEE	Sri Lanka	17	SVM, RF, KNN, MLR
[Rahmati et al. 2020]	2020	ScienceDirect	Viet Nam	40	SVM, CART, RF, BRT, MARS, FDA
[Moumni and Lahrouni 2021]	2021	Hindawi	Morocco	5	ML, ANN, SVM
[Prodhan et al. 2021]	2021	ScienceDirect	China		RF, GBRT
[Gong et al. 2021]	2021	ScienceDirect	China	6	ELR, PSO, GA
[Li et al. 2021]	2021	ScienceDirect	China	2	RF, MLR
[Dubois et al. 2021]	2021	ScienceDirect	France	3	ANN, SVM, RF, DT
[Feyisa et al. 2020]	2020	ScienceDirect	Ethiopia	5	C5.0, SVM, RF
[Yamac¸ and Todorovic 2020]	2020	ScienceDirect	Turkey		AB, ANN, KNN
[Folberth et al. 2019]	2019	ScienceDirect	Austria	48	RF, GBRT

3.2. RQ2 - What algorithms are used for pest, disease or deficiency detection?

Garg *et al.* (2021) used IoT to collect data and apply it to various machine learning algorithms in precision agriculture; among the algorithms used are: RF, light gradient boosting machine (LGBN), XGBoost (XGB), decision tree (DT), KNN and convolutional neural network(CNN), the data used were several, among them irrigation and fertilization aiming to perform the prediction of damage in crops. Shukla *et al.* (2021) Shukla *et al.* (2021) proposed a harvest monitoring system that manages data and devices and supports data sharing and communication by combining IoT and unmanned aerial vehicle (UAV); the combination of IoT and machine learning K-means (KM), ensured the accuracy in predicting harvest diseases.

Agrawal *et al.,* (2021) used machine learning to detect diseases in plantations, the algorithms used were naive bayes (NB) and neural networks (NN). Beck *et al.* (2020) developed a robotic system that captures plants and uses machine learning to identify them from various angles; they could separate and label plants; remove the background and seed images; the authors used CNN. Towett *et al.,* (2020) used machine learning (XGBoost) to quantify the concentrations of nutrient elements (macro and micro) in soil samples and propose a quality control to improve the quality of soil physical condition via organic amendments.

Via machine learning application an ANN and SVM to detect diseases in potato plantations; the experiment was carried out in rural Italy; climatic variables used in the study came from meteorological stations, SVM was more efficient than ANN, Fenu and Malloci (2019). Using Sentinel-2 satellite images, the PLS, RF, and gradient boosted (GB) algorithms were applied to analyze estimates of leaf area and chlorophyll content; RF proved to be better and applicable in crop monitoring, Kganyago *et al.* (2021).

Iatrou *et al.* (2021) carried out the mapping of nitrogen demand in rice planting using XGBoost, treating satellite images (Sentinel 1 and 2), aiming to predict the growth stage. Machine learning algorithms (ANN, RF, and multiple linear regressions (MLR)) was applied to satellite images (Terra MODIS) to identify the insect Nilaparvata lugens, a pest that attacks rice; data crossed with meteorological and satellite information proved to be correct in detecting the pest and developing an alert system, Skawsang *et al.* (2019).

Manrique-Silupu *et al.* (2021) used IoT sensors in banana plantations to estimate pest classification based on machine learning techniques via SVM processing atmospheric data; obtained satisfactory results in the application of spray-on more effective dates. Through the collection of infrared wave data captured in hyperspectral carried out in overflights in corn plantations, these data collected were applied partial least squares (PLS) and RF; indicating the possibility of using data combined with machine learning techniques to quantify planting trails for precision agriculture, Wang *et al.* (2021).

Balakrishna *et al.* (2021) approach realization of the union of IoT with machine learning to detect the invasion of animals in the fields where the plantations are located; used Raspberry PI and cameras with the CNN algorithm to detect animals; detection is sent via Twilio to farmers. Dash *et al.* (2021) approach the establishment of the relationship between micronutrients and macronutrients and climate parameters to classify the crops (rice, wheat, and sugarcane) applied machine learning algorithms SVM and DT.

Danner *et al.* (2021) developed biophysical and biochemical data processing with machine learning algorithms (ANN, RF, SVR, and gaussian process regressions (GPR)) by spectroscopic image analysis; ANN was considered more efficient. Kasinathan et al. (2021) developed an algorithm for detecting insect pests using the dataset (Wang, Xie, Deng, and IP102) through various algorithms (ANN, SVM, KNN, NB, and CNN), CNN proved more efficient.

Hu *et al.* (2020) to identify, control, and predict the levels of heavy metals in crop soils, they used RF and gradient boost (GB) algorithms with variables of soil and crop chemical properties; the authors were able to predict the presence of heavy metals in harvests and reduce time and cost of laboratory analysis of samples. Radhakrishnan (2020) applied the combination of VMS with CNN together to detect the incidence of diseases in rice caused by fungi and bacteria.

The above-mentioned articles are summarized in Table 4 with data from authors, year, parents of the first author, number of citations and main algorithm mentioned in the body of the article; articles related to research question 2.

Table 4. Authors, year, electronic database, citations, algorithm

Author	Year	Database	Country	Citations	Algorithm
[Garg *et al.* 2021]	2021	arXiv	India		RF, LGBM, DT, KNN, CNN, XGB
[Shukla *et al.* 2021]	2021	Microsoft Academic	India		KM
[Agrawal *et al*. 2021]	2021	IEEE	India	87	ANN, NB
[Beck *et al.* 2020]	2020	Plos One	Canada	3	CNN
[Towett *et al.* 2020]	2020	Plos One	Kenya		XGB
[Fenu and Malloci 2019]	2019	ACM	USA		ANN, SVM
[Kganyago *et al*. 2021]	2021	MDPI	South Africa		PLS, RF, GBRT
[Iatrou *et al*. 2021]	2021	MDPI	Greece	1	XGB
[Skawsang et al. 2019]	2019	MDPI	Thailand	7	ANN, RF, MLR
[Manrique-Silupu *et al.* 2021]	2021	ScienceDirect	Peru		SVM
[Wang *et al.* 2021]	2021	ScienceDirect	USA		RF

[Balakrishna *et al.* 2021]	2021	ScienceDirect	India		CNN
[Dash *et al*. 2021]	2021	ScienceDirect	India		SVM, DT
[Danner *et al.* 2021]	2021	ScienceDirect	Germany	8	GPR, ANN, SVR, RF
[Kasinathan *et al.* 2021]	2021	ScienceDirect	India	4	ANN, SVM, KNN, CNN, NB
[Hu *et al.* 2020]	2020	ScienceDirect	China	41	RF, GBRT,
[Radhakrishnan 2020]	2020	ScienceDirect	India	2	SVM, CNN

3.3. RQ3 - What algorithms are used for price prediction?

Yuan *et al.* (2020) proposed a model for commodity price prediction so that government agencies could promote new policies and farmers to improve crop planning. They have developed an algorithm with lag time inspired by a biological evolutionary differential to perform the selection of ideal time for price prediction; the focus is the plantations of Malaysia; (ANN, particle swarm optimization (PSO), and genetic algorithms (GA)).

Ahish *et al.* (2019) analyzed historical data with several regression models (linear, multilinear, and nonlinear) proposing a predictive model for price, which helps in the analysis of the viability of the harvest according to market prices, generating final reports with a graphical representation; (DT, autoregressive integrated moving average (ARIMA)). Chen *et al.* (2021) developed a system for predicting agricultural commodity prices by putting up a web system, where they evaluated several algorithms identifying LST as the best; they applied research in Malaysian market price data; used autoregressive integrated moving average (ARIMA), support vector regression (SVR), Prophet, long short-term memory model (LSTMM), XGBoost.

The above-mentioned articles are summarized in Table 5 with data from authors, year, parents of the first author, number of citations and main algorithm mentioned in the body of the article; articles related to research question 3.

Table 5. Authors, year, electronic database, citations, algorithm

Author	Year	Database	Country	Citations	Algorithm
[Yuan *et al.* 2020]	2020	ACM	Malaysia		ANN, PSO, GA

[N *et al.* 2019]	2019	BASE	India		DT, ARIMA
[Chen *et al.* 2021]	2021	arXiv	Malaysia	1	ARIMA, SVR, Prophet, XGBoost, LSTMM

3.4. RQ4 - What algorithms are used in planning, controlling, and monitoring agricultural production?

Wang *et al.* (2019) proposed an intelligent evaluation method based on machine learning using backpropagation (BP) neural network and support vector machine (SVM) algorithms to establish a high-tech agricultural evaluation index. They indicate that in the area of evaluation of high-tech agriculture, quantitative indices are used, it proposes methods of qualitative analysis according to the experiences of experts in the area using neural networks.

Chaterji *et al.* (2021) collected data through a vast network of IoT devices; presented the Lattice platform, which integrates the IoT devices, processes the data, stores statistics, and presents information about the collected data; used density based spatial clustering of applications with noise (DBSCAN), ANN and Bayesian models (BM). Peppes *et al.* (2021) considers an increase in network attacks on IoT devices and sensors arranged in networks, so you proposed the use of machine learning to perform traffic analysis (employing various algorithms such as KNN, support vector classification (SVC), DT, RF and stochastic descent gradient (SGD)).

To perform the identification of machinery operating in a field, several data were collected about the operation of the machine, seeking to identify which machine works in a given field, the algorithms KNN, SVM, DT, RF, GB were used; the RF showed better results in the classification of machinery, Waleed *et al.* (2021). The authors developed a method that allows the mapping of carrot culture and its yield. The algorithm used was RF, processing data from a satellite spectral database, Wei et al. (2020).

The authors discussed an application of a machine learning algorithm (ID3) to develop an agricultural consultation system (AAS), focusing mainly on soil degradation and crop production, being a recommendation system, Bhimanpallewar and Narasingarao (2020). Concerned about work accidents in the field, the authors Scott *et al.* (2021) used naive Bayes (NB) to identify injuries using an administrative database and pre-hospital data; reduced cases of visual inspection.

Balne (2020) using climate and soil information, inserted in a framework developed as an Android application, this application works together with Multi Linear Regressions (MLR) to indicate the best crop when given soil and climatic conditions. Feng *et al.* (2019) determined that remotely perceived factors contribute to monitoring drought in agriculture (in south-east Australia), using rain and satellite data; three machine learning methods were used RF, SVM, and multi-layer perceptron neural network (MLPNN); RF was the one that showed the best results.

Jagtap *et al.* (2021) presented the applicability of several methods of machine learning in agriculture, among them KNN, Bayesian model (BM), ANN, CNN, DT, RF, and SVM), indicating the possibility of economic applicability in various areas of agriculture. The authors Mouhssine *et al.* (2020) proposed to use machine learning to classify red fruits from a farm without human intervention were used KNN, deep neural networks, and CNN.

Muthoni *et al.* (2021) estimated temporal variations in maize grains over 13 years in four African countries; applying RF on several variables (such as rain and humidity) could detect variations in the grains; indicate that data from various sources coupled with machine learning algorithms can be used to predict actions and aid agriculture. Liu and Zhan (2019) studied the financial efficiency of listed Chinese agricultural companies using RF machine learning and the Tobit regression model; RF stands out; the authors point out which indicators improve the performance of companies.

Adebiyi *et al.* (2020) developed a mobile support system that uses machine learning to optimize land use; this system receives various input data such as geolocation, soil type, and crop; using RF classifies cultures according to their application, used solutions to develop such as BigML e Appery.io. Tang *et al.* (2020) proposed a multiscale object-based weighted method classification method with manual digitization of harvest distribution in Gaofeng-2 satellite images.

Sosa *et al.* (2021) proposed the assessment of hail damage in crops using machine learning with KM clustering pixel of damaged areas in Sentinel1 and 2 satellite images; applied the study to corn, soybeans, and wheat. Acharya *et al*. (2021) conducted studies with machine learning algorithms to predict soil mix, including CART, RF, BRT, MLR, SVR, and ANN; the authors indicate better performance for RF and BRT.

Banerjee *et al.* (2021) developed methods to estimate wheat seedlings using multispectral images captured from unmanned aerial vehicles (drones); the algorithms were regression trees, support vector, and Gaussian regression; show promising results at 10 m altitude with 20-day seedlings. Crisostomo de Castro Filho *et al.* (2020) carried out the mapping of rice plantations via satellite images (Sentinel-1) processed via machine learning with ANN and LSTM and compared with SVM, RF, KNN, and NB; a bidirectional long short-term memory (LSTM) proved to be more accurate.

Abbas *et al.* (2020) applied proximal sensing techniques to investigate soil and crops in potato cultivation, including machine learning with KNN, SVR, and linear regression; conclude that a vast and broad database is needed to generate more accurate results for each model that can be applied in specific areas. Ding *et al.* (2020) evaluated machine learning regression machines using multispectral data from Sentinel-2 satellite and unmanned aerial vehicles; partial least squares regression (PLSR), ANN, Gaussian process, SVR, and RF were analyzed; and the recommended approach was Gaussian processes to quantify crop residue coverage.

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Maimaitijiang *et al.* (2020) the combination of data from satellites (Worldview-2/3) and unmanned aerial vehicles and machine learning was performed; PLSR, RFR, SVR, and ELR algorithms were used; studies focus on soy plantations and indicate that combining diverse image data with machine learning techniques increases crop monitoring opportunities. Machine learning application via gray level cooccurrence matrix (GLCM), RF, and SVM on images captured by unmanned aerial vehicles allowed for crop classification; the results indicate that only one image is used for crop classification, Kwak and Park (2019).

Yang *et al.* (2019) indicates that data from remote sensors can be allocated in grids for crop classification; applying parallel computation techniques increased the computation capacity on the grid; used data from Gaofen and Sentinel satellite images submitted to machine learning with SVM and RF; they end by indicating that parallel computing helps in the data processing. Zhang *et al.* (2019) used KNN, RF, and SVM algorithms under a spectral database aiming at harvest classification; the data crossing also used crop classifiers; created a spectral library combined with the characteristics of cultures allowing for remote monitoring.

Mateo-Sanchis *et al.* (2021) aimed to investigate the agro-ecological influence and regions of influence to estimate harvest using gaussian process regression (GPR), the combination of variables such as soil and vegetation, and their relationship in the model that allows identifying anomalous crops and their failure factors. Tufail *et al.* (2021) used multispectral data from Synthetic Aperture Radar and Multispectral Instruments from Sentinel 1 and 2 satellites with RF algorithms to perform a mapping of crop types and used DT in the study of land use.

Pant *et al.* (2021) a machine learning approach (gradient boosted (GB), RF, SVM, and DT) was used to develop a model capable of identifying patterns in corn, potato, rice, and wheat crop data, seeking to identify patterns for crop prediction. Paudel *et al.* (2021) performed the combination of crop modeling with machine learning (KNN), including climate, soil, and remote sensing data; five crops were studied: wheat, barley, sunflower, sugar cane, and potato), the increase in data indicates greater and better results in the forecasts.

Maponya *et al.* (2020) used satellite images (Sentinel-2) to classify harvest types using the algorithms (SVM, DT, KNN, RF, and ML), indicating that SVM and RF obtained better results than other algorithms. Schwalbert *et al.* (2020) to improve soybean crop forecasts, they used LSTM and RF applied to satellite images and variables such as soil temperature and precipitation, demonstrating the possibility of integrating statistics with remote sensing.

Wolanin *et al.* (201) performed the analysis of satellite images (Landsat 8 and Sentinel-2) applying machine learning with neural networks (ANN) to estimate crop yield for C3 and C4 crops. Tao and You *et al.* (2019) used multi-layer perceptron neural network (MLPNN)) and neural networks applied (ANN) to satellite images to perform prediction of adoption of cover crop adoption for the corn crop.

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The above-mentioned article sums up in table 6 with data from authors, year, parents of the first author, number of citations and main algorithm mentioned in the body of the article; articles related to research question 4.

Table 6. Authors, year, electronic database, citations, algorithm

Author	Year	Database	Country	Citations	Algorithm
[Wang et al. 2019]	2019	ACM	China		ANN, SVM
[Chaterji et al. 2021]	2021	IEEE	USA	2	DBSCAN, ANN, BM
[Peppes et al. 2021]	2021	MDPI	Greece		KNN, SVC, DT, RF SGD
[Waleed et al. 2021]	2021	MDPI	Korea	2	KNN, SVM, DT, RF, GB
[Wei et al. 2020]	2020	MDPI	Brazil	7	RF
[Bhimanpallewar and Narasingarao 2020]	2020	IEEE	India	1	ID3
[Scott et al. 2021]	2021	Springer	USA		NB
[Balne 2020]	2020	Microsoft Academic	India		MLR
[Feng et al. 2019]	2019	ScienceDirect	Australia	57	MLPNN, SVM, RF
[Jagtap et al. 2021]	2021	ScienceDirect	India		SVM, RF, DT, KNN, CNN, BM, KM
[Mouhssine et al. 2020]	2020	Microsoft Academic	Morocoo		KNN, CNN
[Muthoni et al. 2021]	2021	IEEE	Tanzania	31	RF
[Liu and Zhan 2019]	2019	Hindawai	China	9	RF
[Adebiyi et al. 2020]	2020	Hindawai	Nigeria	7	RF
[Tang et al. 2020]	2020	IEEE	China	2	SVM
[Sosa et al. 2021]	2021	MDPI	Spain		KM

[Acharya et al. 2021]	2021	MDPI	USA		ANN, SVR, CART, RF, BRT, MLR
[Banerjee et al. 2021]	2021	MDPI	Australia		GPR, SVM, CART
[Crisostomo de Castro Filho et al. 2020]´	2020	MDPI	Brazil	22	ANN, LSTMM
[Abbas et al. 2020]	2020	MDPI	Canada	17	EN, SVR, KNN
[Ding et al. 2020]	2020	MDPI	China	4	GPR, PLSR, ANN, SVM, RF
[Maimaitijiang et al. 2020]	2020	MDPI	USA	27	PLSR, SVR, ELR, RF
[Kwak and Park 2019]	2019	MDPI	Korea	29	GLCM, SVM, RF
[Yang et al. 2019]	2019	MDPI	China	27	SVM, RF
[Zhang et al. 2019]	2019	MDPI	China	9	SVM, RF, KNN
[Mateo-Sanchis et al. 2021]	2021	ScienceDirect	Spain		GPR
[Tufail et al. 2021b]	2021	ScienceDirect	Pakistan		RF, DT
[Pant et al. 2021]	2021	ScienceDirect	India		SVM, RF, DT, GBRT
[Paudel et al. 2021]	2021	ScienceDirect	Netherlands	4	KNN
[Maponya et al. 2020]	2020	ScienceDirect	South Africa	19	ML, SVM, RF, DT, KNN
[Schwalbert et al. 2020]	2020	ScienceDirect	Brazil	44	RF, LSTMM
[Wolanin et al. 2019]	2019	ScienceDirect	Germany	47	ANN
[Tao and You 2019]	2019	ScienceDirect	USA	1	ANN, MLPNN, RF

3.5. RQ5 - What technologies are used in conjunction with machine learning?

Mazzia *et al* (2020) presented a framework for satellite image processing using deep learning techniques and the use of unmanned aerial vehicles; the classifier algorithm used was KM. Abdellah and Thangadurai (2021) developed an IoT framework so farmers could view their data remotely; used the Blynk IoT platform receiving data from Raspberry Pi; allowing them to start the irrigation process, suggest fertilizers, and detect moving objects in the plantation by capturing images.

Gumma *et al.* (2020) used RF to create a Landsat satellite image bank and process the algorithm in the Google Earth Engine cloud; this big data presented a vast picture of Southeast Asia's agricultural production. Tufail *et al.* (2021) developed equipment for the intelligent application of agrochemicals in tobacco plating; the equipment can be installed on a tractor; machine learning used the SVM classifier running on a Raspberry Pi. Shafi *et al.* (2020) present a proposal for the integration of technologies: IoT, machine learning, and Drones to allow the analysis of harvest health; the proposal unifies data collected from IoT sensors with multispectral data collected by drones; the data are later validated via field specialist.

Aneece and Thenkabail (2021) used historical data from Earth Observing-1 (EO-1) with data from the DLR Earth Sensing Imaging Spectrometer via machine learning in Google Earth Engine to classify crops in the USA; the algorithms used were RF, SVM, NB and WekaXMeans; the use of cloud computing associated with machine learning facilitates the analysis and classification in agriculture. Worrall *et al.* (2021) used machine learning via LSTMM and ANN to estimate corn harvest growth, developing the domain guided neural network (DgNN) method that includes domain knowledge.

Yang and Cho (2021) developed a solution for rebuilding 3D images of plants from 2D images captured with Microsoft Kinect V2, applying machine learning algorithms such as DBSCAN and KM; several other algorithms for image treatment were used; the combination of these demonstrated errors below 5mm in the reconstruction of 3D images. Barnes *et al.* (2021) isolated photosynthetic activity signal via satellite images by machine learning application using RF; incorporated thermal data and reflectance metrics.

Najafi *et al.* (2021) performed the comparison of image analysis methods via Fuzzy analysis and methods of machine learning algorithms (SVM and ANN) aiming to analyze the vegetation residue coverage; unmanned vehicles and satellite (Sentinel-2) were used. Xie *et al.* (2021) performed the harvest height estimation with PolSAR and RADARSAT-2 radar images in agricultural areas of Canada; the data were applied to the RF and SVR methods; RF had the best results in obtaining height data from the radar.

Momm *et al.* (2020) Developed a procedure to generate a history of crop types from vegetation index data collected from satellite (Landsat 5); this data was applied evaluated via RF algorithm, the crops studied were corn and soybean. Yan *et al.* (2021) presented a method for merging images of multiple satellites (Sentinel-2 and GaoFen-1) to observe time-space data by applying a grid framework; used machine learning via classification and regression trees (CART) aiming at the classification of crops.

Using the same types of input variables with data on rice, corn, and soybean crops, and seven machine learning algorithms were evaluated (SVM, DT, RF, ANN, stacked sparse autoencoder (SSAE), CNN, and long short-term memory (LSTM)); identifying the SVM as the efficient, Ju *et al*. (2021) [Ju *et al.* 2021]. By using satellite images (Sentinel 1 and 2) to monitor portions of arable area in Germany, RF was used to classify regions for green emissions, data with normalized difference vegetation index (NDVI) were used as input, the final model can be adapted to other types of datasets, Schulz *et al.* (2021).

The above-mentioned articles are summarized in table 7 with data from authors, year, parents of the first author, number of citations and main algorithm mentioned in the body of the article; articles related to research question 6.

Table 7. Authors, year, electronic database, citations, algorithm

Author	Year	Database	Country	Citations	Algorithm
[Mazzia et al. 2020]	2020	MDPI	Italy	23	KM
[Abdellah and Thangadurai 2021]	2021	IEEE	Sudan	62	CNN
[Gumma et al. 2020]	2019	Tandfonline	USA		RF
[Tufail et al. 2021a]	2021	IEEE	Pakistan		SVM
[Shafi et al. 2020]	2020	IEEE	Pakistan	6	SVM, NB
[Aneece and Thenkabail 2021]	2021	MDPI	USA		WekaXMeans, SVM, RF, NB
[Worrall et al. 2021]	2021	MDPI	USA		ANN, LSTMM
[Yang and Cho 2021]	2021	MDPI	Korea	57	MSC, DBSCAN, KM
[Barnes et al. 2021]	2021	MDPI	USA		RF
[Najafi et al. 2021]	2021	MDPI	Iran	7	ANN, SVM
[Xie et al. 2021]	2021	MDPI	China	7	SVR, RF
[Momm et al. 2020]	2020	MDPI	USA	7	RF
[Yan et al. 2021]	2021	ScienceDirect	China	1	CART

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[Ju et al. 2021]	2021	ScienceDirect	South Korea		SSAE, SVM, RF, DT, CNN, LSTMM
[Schulz et al. 2021]	2021	ScienceDirect	Germany	1	RF

3.6. RQ6 - Is it possible to elaborate on a basic taxonomy?

After collecting the articles and studying them, we investigate what is being used and pointed out by the researchers, which allowed the elaboration of a primary taxonomy presented in Figure 3. This taxonomy allows for analysis and comparisons with the latest machine learning application in agriculture. First, we present the main crops dealt with in the articles, indicating that they are mostly export commodities. Next, we indicate the cloud technologies used. Finally, we indicate that remote sensing is extensively explored in several articles. The algorithms could have been elaborated and grouped by family category, but we decided to list them here as the authors cite them in the articles. The taxonomy was designed from the collected articles; we can observe five significant ramifications (applicability, cultures and technologies, and machine learning); machine learning was subdivided into supervised and unsupervised algorithms. The technologies were subdivided into cloud, UAV, IoT, and remote sensing; in UAV, we have drones that perform data collection via aero photogrammetry, in Cloud Google Earth stands out; in IoT, the most popular microcontroller is the Raspberry Pi; in remote sensing, the most cited satellites are Sentinel 1 and 2.

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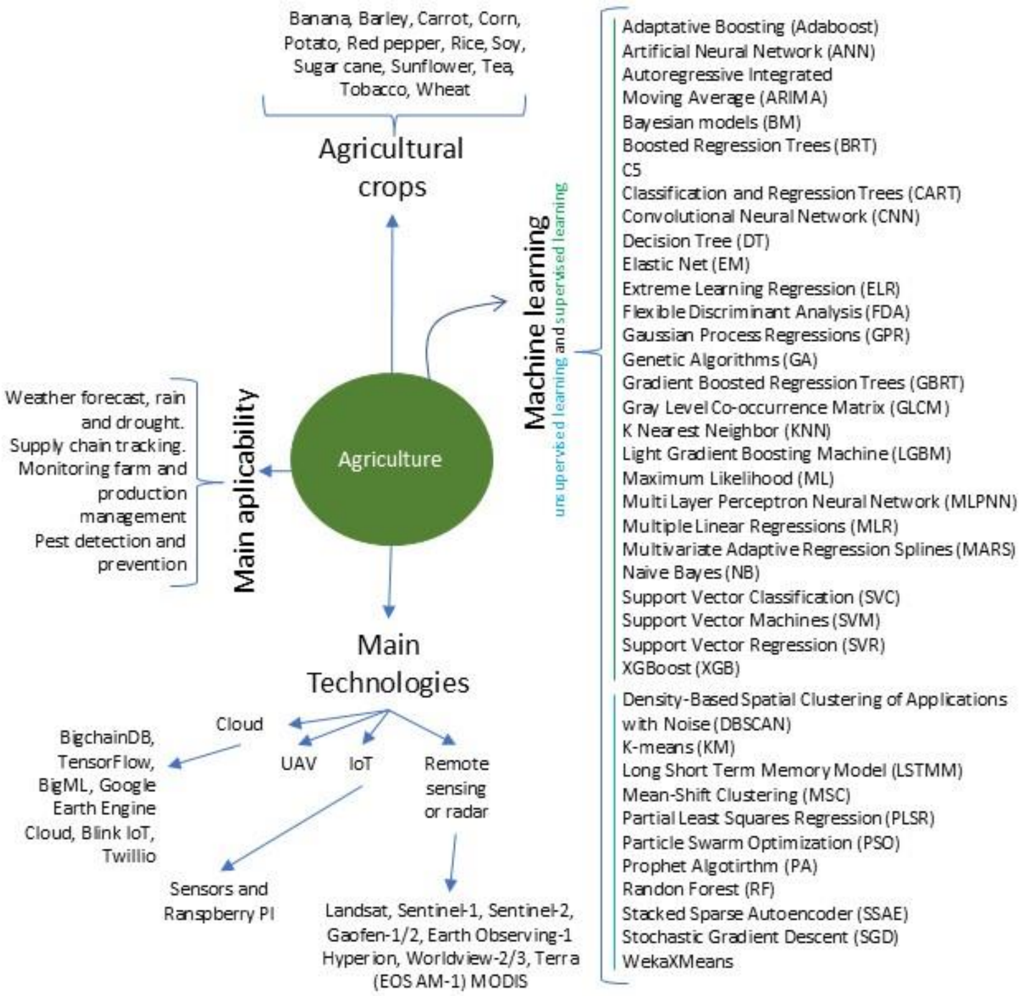

Figure 3. Basic taxonomy

3.7. RQ7 - What other bibliometric data can be obtained?

Several algorithms are mentioned during the work, we list the 10 most identified by the authors, they are by quantities: random forest (RF) - 40, support vector machines (SVM) - 25, artificial neural network (ANN) - 18, decision tree (DT) - 12, K nearest neighbor (KNN) - 11, convolutional neural network (CNN) 9, support vector regression (SVR) - 7, K-means (KM) 5, long short term memory model (LSTMM) - 5, naive Bayes (NB) - 5, see Figure 4. In addition to the technologies mentioned in question 6, we can see satellites mentioned in other articles with another focus, but if we add them all together, the quantities are: Landsat - 5, Sentinel-1 - 7, Sentinel-2 11, Gaofen-1/2 - 4, Earth Observing - 3, Worldview-2/3 - 2 and Terra - 3, see Figure 5.

Also, nine articles cited the use of technologies such as IoT, Arduino and Raspberry Pi. Eight articles cited the use of UAV (Unmanned Aerial Vehicle). Fifteen articles addressed topics related to Agriculture 4.0. The most cited crops are banana, barley, carrot, corn, potato, red pepper, rice, soy, sugar cane, sunflower, tea, tobacco, wheat; it is important to note that soybeans, corn, and wheat are

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high-value agricultural commodities for export. Also, it was considered the country of the first author; then we ranked the top 10 countries with the highest number of publications: China - 16, India - 14, USA - 13, Brazil - 4, Germany - 3, Korea - 3, Pakistan - 3, Australia - 2, Canada - 2, Greece - 2; see Figure 6.

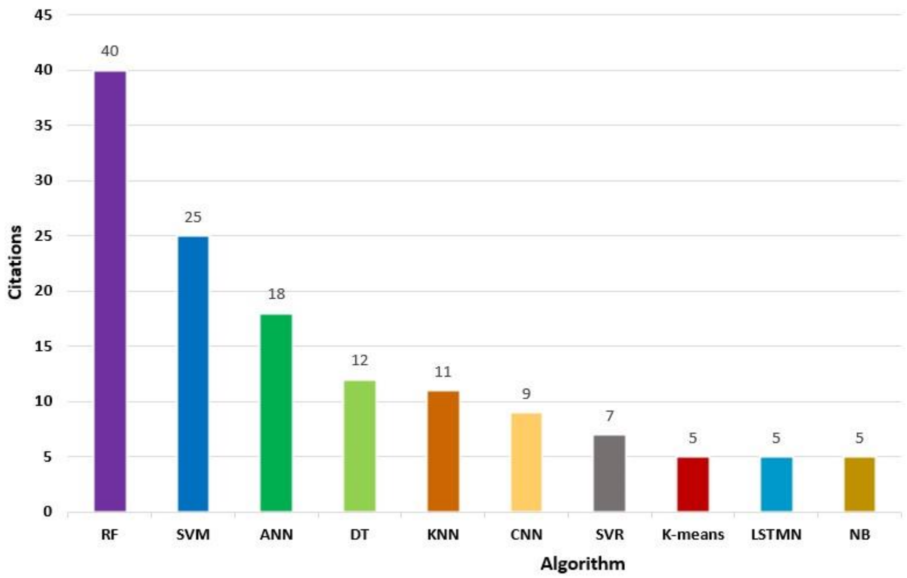

Figure 4. Top 10 most cited algorithm

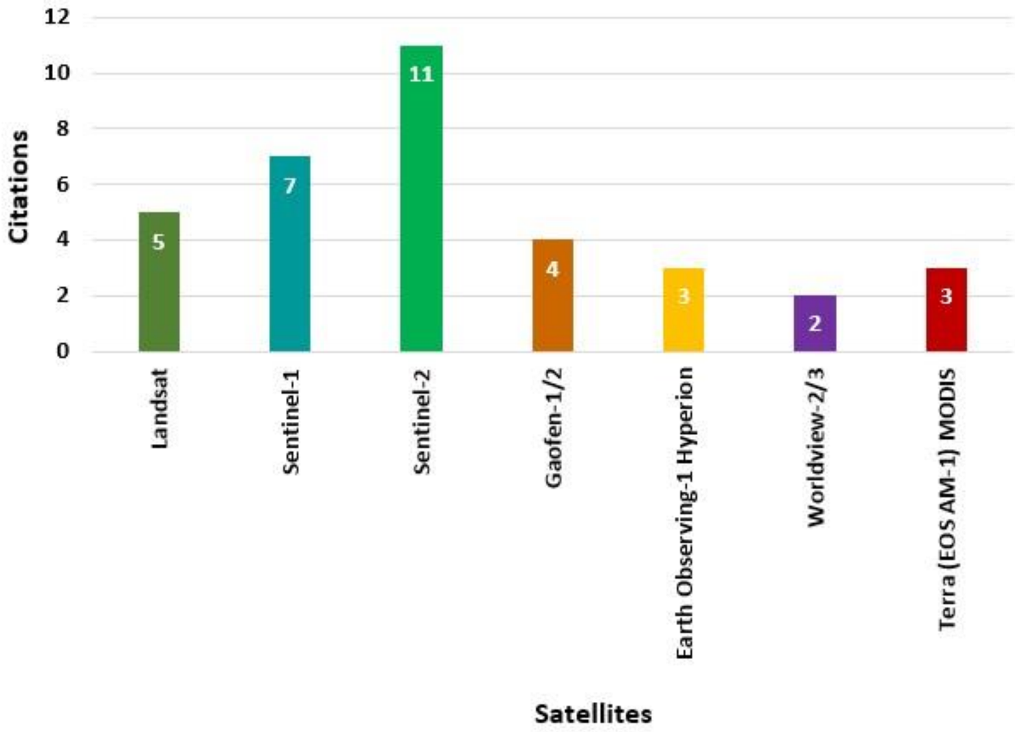

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Figure 5. Satellites most cited

Figure 6. Top 10 countries with the major publications

3.8. Overview of word cloud

We present an overview of various keywords and their relationship and limitations of this search. The software used to build bibliometric networks was VOSviewer (Waltman *et al.* 2010) and (van Eck; Waltman, 2009). The text was extracted from the title and abstract from a .RIS file. The references of each article were used in. RIS format to feed the Vosviewer tool. Full counting was chosen as a method. Of 2175 terms, 34 meet the threshold, and seven minimum occurrences of a term were selected. The number of terms selected was 40. Figure 7 presented do word grouping in words clusters and its interrelation. The clusters detected by VOSviewer were: Cluster 1: approach, crop yield, input, machine learning, model, prediction, random forest, region, remote sensing, rice, rmse, study, technique; Cluster 2: agriculture, algorithm, application, data, farmer, iot, machine, machine learning algorithm, paper, soil, time, type; Cluster 3: accuracy, classification, crop, experiment, image, information, sentinel, support vector machines, use.

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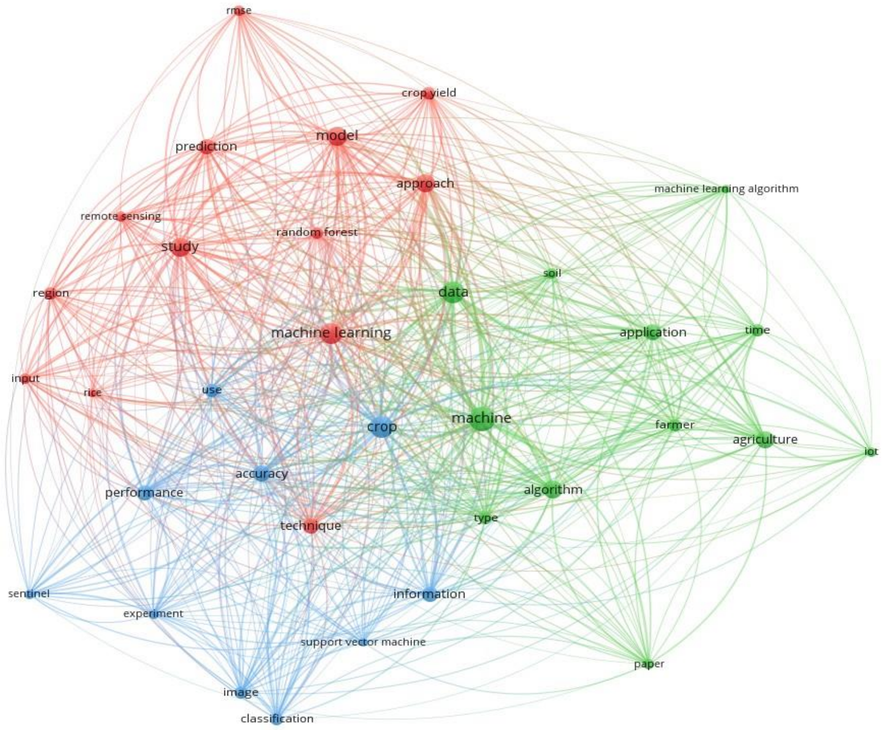

Figure 7. Word cloud and its interrelationships in clusters

We can extract from Figure 7 that the term machine learning algorithm is quite strong seen in the detail of Figure 8, in the same way the term random forest can be seen separately in Figure 9.

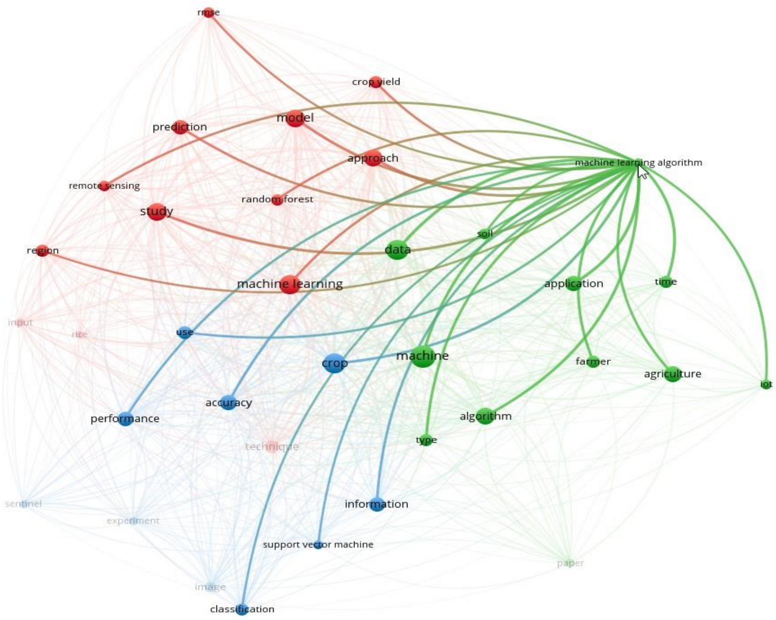

Figure 8. Detail of potential relationships between with "machine learning algorithm"

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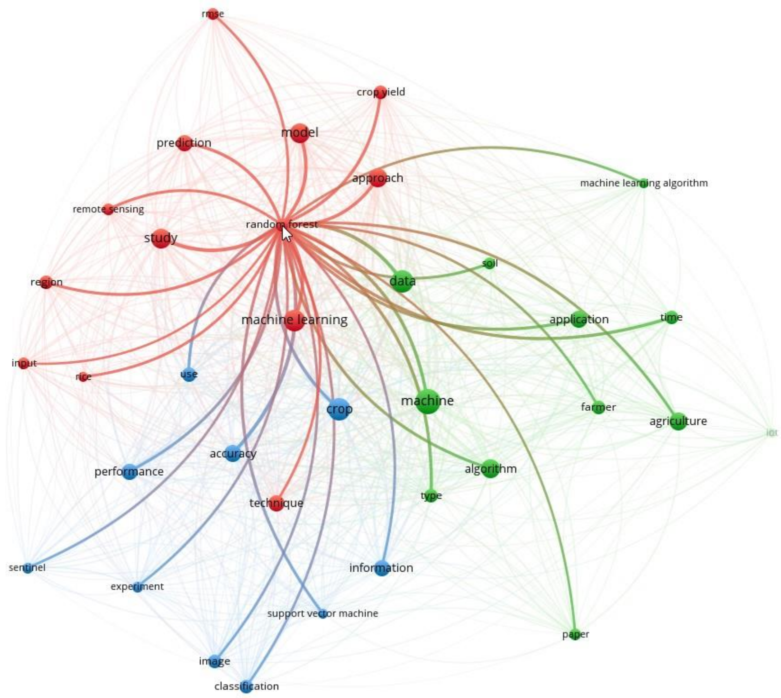

Figure 9. Detail of potential relationships between with "random forest"

4. LIMITATIONS

We tried to investigate the application of machine learning in agriculture. This article is limited to the application of machine learning in agriculture only, not addressing secondary issues such as social and other fields of artificial intelligence beyond the one addressed by the authors of the selected articles. Our focus was on applying machine learning within a previously defined temporal window. Another limitation was the issue of acquiring articles exclusively via databases of scientific portals. Thus, it is possible that some articles have not entered the search radar because we removed other databases. The extraction of data, duplicates, title, and abstract was performed with the help of a large data table and manually; in this way, as quoted by Rattan *et al.* (2013), errors can occur even due to the loss of articles; efforts were made to mitigate this possibility.

5. RESEARCH QUESTIONS: COMMENTARY AND FINDINGS

Question 1 pointed out the theme of drought, water resource management, and climate forecasting; includes the weather forecast on this issue along with the issue of drought because through the predictability of rains, farmers and government entities can carry out planning against events such as drought; several algorithms are used highlighting RF and SVM, the focus of the analyzed articles mostly deals with large crops such as (rice, wheat, potato and corn) and in cases where Landsat and Sentinel satellite images stand out, indicating the possibility of a greater number of projects focusing on data collection in the field with IoT devices, treatment of incomplete climatic data series.

Question 2 pointed to the needs of farmers to fight different types of pests, from microscopic ones, insects to larger animals; several studies use satellite images to detect, via multispectral images, possible variations and diseases in crops, only one work showed the identification of larger animals and one in the identification of insects, which shows the need to expand studies and tests in fields of intelligent traps. Allied to machine learning and warning systems; only one study performed an IoT mix with alerts via messaging; Here, the crops studied are high-value commodities for export, such as soybeans and corn (among others), which indicates the authors' preference for serving these crops and to the detriment of the micro family farmer, which is also an open opportunity due to the low investment power.

Question 3 indicates a few works aimed at forecasting prices or forecasting gains with the harvest; we indicate as an open question the use of data collected in the field and the use of socio-economic data series for the region studied with global market data.

Question 4 presents how the technology can be applied in various internal aspects of the farm, its controls, monitoring, and planning; several aspects are taken into consideration, such as safety, safety at work, analysis of financial efficiency, plant coverage, harvest prediction, classification of harvests (and grains) among others; we note the possibility of exploring the collection and integration of telemetry data from agricultural machinery and the need for expansion in communication technologies for the field, as without these the exchange of data between systems would be unfeasible, more studies are needed in these areas.

Question 5 presents several technological resources in use, mainly unmanned aerial vehicles (UAV) and satellites; Other articles deal with satellites, we group ed in question 6 the most relevant; however, it is an open field to use robots within the fields combined with cloud technologies (little explored), once again this field of study touches the issue of field connectivity.

Question 6 presents a brief taxonomy, indicating the algorithms cited in the studies, indicating the possibility of exploring several other areas such as: including economic, socio-economic data, risk analysis for production based on multiple social, pandemic, climatic, and market scenarios; in addition to data on the use of new technologies in the field such as 5G and increased use of robots in agriculture.

6. CONCLUSIONS

The current study carried out a literature review to identify the use of machine learning in agriculture (the complete list of articles is listed in Appendix 1). We answer several research questions. We identify and organize results in a structured way in the document according to the questions. We suggest several other fields of study in the open questions section. We have included a basic taxonomy indicating the identified technologies; this is important as it presents what has been used with machine learning and in the years of 2019-2021, updated and recent. As for recommendations for future work, we recommend: 1) a macro model or architecture that includes the new horizons pointed out in the open questions section; 2) a service that can be pointed to a folder where there are satellite images and pointed to a database where there are series of tabular data, this service can run in the background mode and have a graphical interface for its configuration, the service output would be tables and graphics processed from the input data, this service would allow its user to choose the data source, algorithm type and output type (table or graph); 3) Analyze the use of large language models such as BERT and how these models are impacting field data analysis for farmers and agricultural problem researchers and 4) Developing a macro model or framework for applying AI in agriculture arose from the need to integrate various technologies (such as IoT, big data, machine learning, and computer vision) into a unified architecture.

7. FUNDING

This research received no funding.

8. CONFLICTS OF INTEREST

The authors declare no conflict of interest.

9. ABBREVIATIONS USED IN THIS MANUSCRIPT

AAB – Adaboost Adaptative Boosting
ANN – Artificial Neural Network
ARIMA – Autoregressive Integrated Moving Average
BM – Bayesian models
BRT – Boosted Regression Trees
C5 – C5.0 algorithm
CART – Classification and Regression Trees
CNN – Convolutional Neural Network
DBSCAN – Density-Based Spatial Clustering of Applications with Noise
DGNN – Domain Guided Neural Network
DT – Decision Tree
ELR – Extreme Learning Regression
EM – Elastic Net
FDA – Flexible Discriminant Analysis
GA – Genetic Algorithms
GB – Gradient Boosting
GBRT – Gradient Boosted Regression Trees

GLCM – Gray Level Co-occurrence Matrix

GPR – Gaussian Process Regressions

KNN – K Nearest Neighbor

KM – K-means

LGBM – Light Gradient Boosting Machine

LLM –Large Language Models

LSTMM – Long Short Term Memory Model

MARS – Multivariate Adaptive Regression Splines

ML – Maximum Likelihood

MLPNN – Multi Layer Perceptron Neural Network

MLR – Multiple Linear Regressions

MODIS – Moderate Resolution Imaging Spectrometer

MSC – Mean-Shift Clustering

NB – Naive Bayes

NDVI – Normalized Difference Vegetation Index

PLS – Partial Least Squares

PSO – Particle Swarm Optimization

PA – Prophet Algotirthm

RF – Random Forest

SSAE – Stacked Sparse Autoencoder

SGD – Stochastic Gradient Descent

SVC – Support Vector Classification

SVM – Support Vector Machines

SVR – Support Vector Regression

XGB – XGBoost Extreme Gradient Boosting

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