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Crop yield prediction using machine learning: A systematic literature review

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ABSTRACT

Machine learning is an important decision support tool for crop yield prediction, including supporting decisions on what crops to grow and what to do during the growing season of the crops. Several machine learning algorithms have been applied to support crop yield prediction research. In this study, we performed a Systematic Literature Review (SLR) to extract and synthesize the algorithms and features that have been used in crop yield prediction studies. Based on our search criteria, we retrieved 567 relevant studies from six electronic databases, of which we have selected 50 studies for further analysis using inclusion and exclusion criteria. We investigated these selected studies carefully, analyzed the methods and features used, and provided suggestions for further research. According to our analysis, the most used features are temperature, rainfall, and soil type, and the most applied algorithm is Artificial Neural Networks in these models. After this observation based on the analysis of machine learning-based 50 papers, we performed an additional search in electronic databases to identify deep learning-based studies, reached 30 deep learning-based papers, and extracted the applied deep learning algorithms. According to this additional analysis, Convolutional Neural Networks (CNN) is the most widely used deep learning algorithm in these studies, and the other widely used deep learning algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN).

1. Introduction

Machine learning (ML) approaches are used in many fields, ranging from supermarkets to evaluate the behavior of customers (Ayodele, 2010) to the prediction of customers' phone use (Witten et al., 2016). Machine learning is also being used in agriculture for several years (McQueen et al., 1995). Crop yield prediction is one of the challenging problems in precision agriculture, and many models have been proposed and validated so far. This problem requires the use of several datasets since crop yield depends on many different factors such as climate, weather, soil, use of fertilizer, and seed variety (Xu et al., 2019). This indicates that crop yield prediction is not a trivial task; instead, it consists of several complicated steps. Nowadays, crop yield prediction models can estimate the actual yield reasonably, but a better performance in yield prediction is still desirable (Filippi et al., 2019a).

Machine learning, which is a branch of Artificial Intelligence (AI) focusing on learning, is a practical approach that can provide better yield prediction based on several features. Machine learning (ML) can determine patterns and correlations and discover knowledge from datasets. The models need to be trained using datasets, where the outcomes are represented based on past experience. The predictive model is built using several features, and as such, parameters of the models are determined using historical data during the training phase. For the testing phase, part of the historical data that has not been used for training is used for the performance evaluation purpose.

An ML model can be descriptive or predictive, depending on the research problem and research questions. While descriptive models are used to gain knowledge from the collected data and explain what has happened, predictive models are used to make predictions in the future (Alpaydin, 2010). ML studies consist of different challenges when aiming to build a high-performance predictive model. It is crucial to select the right algorithms to solve the problem at hand, and in addition, the algorithms and the underlying platforms need to be capable of handling the volume of data.

To get an overview of what has been done on the application of ML in crop yield prediction, we performed a systematic literature review (SLR). A Systematic Literature Review (SLR) shows the potential gaps in research on a particular area of problem and guides both practitioners and researchers who wish to do a new research study on that problem area. By following a methodology in SLR, all relevant studies are accessed from electronic databases, synthesized, and presented to respond to research questions defined in the study. An SLR study leads to new perspectives and helps new researchers in the field to understand the state-of-the-art.

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An SLR study is expected to be replicable, which means that all the steps taken need to be explained clearly, and the results should be transparent for other researchers. The critical factors for a successful SLR study are objectivity and transparency (Kitchenham et al., 2007). As its name indicates, an SLR needs to be systematic and cover all the literature published so far. This study presents all the available literature published so far on the application of machine learning in crop yield prediction problem. In this study, we present our empirical results and responses to the research questions defined as part of this review article.

The remainder of this paper is organized as follows: Section 2 explains the background. Section 3 discusses the methodology. Section 4 presents the results of the SLR. Section 5 explains the deep learning-based crop yield prediction research. Section 5 presents the discussion, and Section 7 concludes this paper.

2. Related work

Crop yield prediction is an essential task for the decision-makers at national and regional levels (e.g., the EU level) for rapid decision-making. An accurate crop yield prediction model can help farmers to decide on what to grow and when to grow. There are different approaches to crop yield prediction. This review article has investigated what has been done on the use of machine learning in crop yield prediction in the literature.

During our analysis of the retrieved publications, one of the exclusion criteria is that the publication is a survey or traditional review paper. Those excluded publications are, in fact, related work and are discussed in this section. Chlingaryan and Sukkarieh performed a review study on nitrogen status estimation using machine learning (Chlingaryan et al., 2018). The paper concludes that quick developments in sensing technologies and ML techniques will result in cost-effective solutions in the agricultural sector. Elavarasan et al. performed a survey of publications on machine learning models associated with crop yield prediction based on climatic parameters. The paper advises looking broad to find more parameters that account for crop yield (Elavarasan et al., 2018). Liakos et al. (2018) published a review paper on the application of machine learning in the agricultural sector. The analysis was performed with publications focusing on crop management, livestock management, water management, and soil management. Li, Lecourt, and Bishop performed a review study on determining the ripeness of fruits to decide the optimal harvest time and yield prediction (Li et al., 2018). Mayuri and Priya addressed the challenges and methodologies that are encountered in the field of image processing and machine learning in the agricultural sector and especially in the detection of diseases (Mayuri and Priya, xxxx). Somvanshi and Mishra presented several machine learning approaches and their application in plant biology (Somvanshi and Mishra, 2015). Gandhi and Armstrong published a review paper on the application of data mining in the agricultural sector in general, dealing with decision making. They concluded that further research needs to be done to see how the implementation of data mining into complex agricultural datasets could be realized (Gandhi and Armstrong, 2016). Beulah performed a survey on the various data mining techniques that are used for crop yield prediction and concluded that the crop yield prediction could be solved by employing data mining techniques (Beulah, 2019).

According to our survey of review articles, the significant ones of which are presented in this section, this paper is the first SLR that focuses on the application of machine learning in the crop yield prediction problem. The existing survey studies did not systematically review the literature, and most of them reviewed studies on a specific aspect of crop yield prediction. Also, we presented 30 deep learning-based studies in this article and discussed which deep learning algorithms have been used in these studies.

3. Methodology

3.1. Review protocol

Before conducting the systematic review, a review protocol is defined. The review has been done using the well-known review guidelines provided by Kitchenham et al. (2007). Firstly, the research questions are defined. When research questions are ready, databases are used to select the relevant studies. The databases that were used in this study are Science Direct, Scopus, Web of Science, Springer Link, Wiley, and Google Scholar. After the selection of relevant studies, they were filtered and assessed using a set of exclusion and quality criteria. All the relevant data from the selected studies are extracted, and eventually, the extracted data were synthesized in response to the research questions. The approach we followed can be split up into three parts: plan review, conduct review, and report review.

The first stage is planning the review. In this stage, research questions are identified, a protocol is developed, and eventually, the protocol is validated to see if the approach is feasible. In addition to the research questions, publication venues, initial search strings, and publication selection criteria are also defined. When all of this information is defined, the protocol is revised one more time to see if it represents a proper review protocol. In Fig. 1, the internal steps of the Plan Review stage are represented.

The second stage is conducting the review, which is represented in Fig. 2. When conducting the review, the publications were selected by going through all the databases. The data was extracted, which means that their information regarding authors, year of publication, type of publication, and more information regarding the research questions were stored. After all the necessary data was extracted correctly, the data was synthesized in order to provide an overview of the relevant papers published so far.

In the final stage, a.k.a., Reporting the Review, the review was concluded by documenting the results and addressing the research questions, as shown in Fig. 3.

3.2. Research questions

This SLR aims to get insight into what studies have been published in the domain of ML and crop yield prediction. To get insight, studies have been analyzed from several dimensions. For this SLR study, the following four research questions(RQs) have been defined.

- RQ1- Which machine learning algorithms have been used in the literature for crop yield prediction?
- RQ2- Which features have been used in literature for crop yield prediction using machine learning?
- RQ3- Which evaluation parameters and evaluation approaches have been used in literature for crop yield prediction?
- RQ4- What are challenges in the field of crop yield prediction using machine learning?

3.3. Search strategy

The searching is done by narrowing down to the basic concepts that are relevant for the scope of this review. Machine learning has many

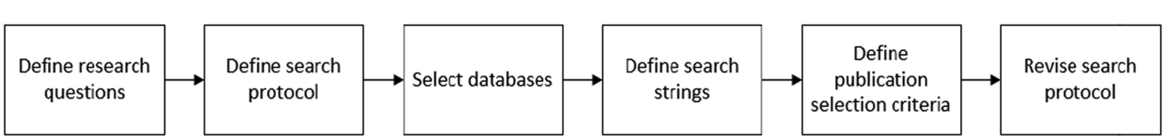

Fig. 1. Details of the Plan Review Step.

Fig. 2. Details of the Conducting Review Step.

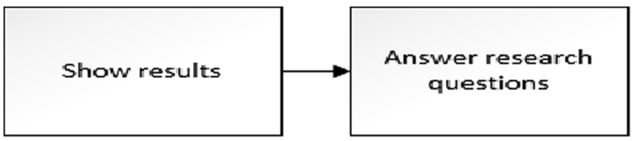

Fig. 3. Details of the Reporting Review Step.

application fields, which means that there are a lot of published studies that are probably not in the scope of this review article. The basic searching is done by an automated search. The starting input for the search was "machine learning" AND "yield prediction". Articles were retrieved, and abstracts were read to find the synonyms of the keywords. The search was performed in six databases. The search input "machine learning" AND "yield prediction" was used to get a broad view of the studies. After the exclusion criteria were applied, and all the results were processed, and a more complex search string was built in order to avoid missing relevant studies. This final search string is as follows: (("machine learning" OR "artificial intelligence") AND "data mining" AND ("yield prediction" OR "yield forecasting" OR "yield estimation")). After executing this search string, 567 studies were retrieved.

A specific description of the search strings per database are provided as follows:

Science direct: The search string is ["machine learning" AND "yield prediction"] (Title, abstract, keywords) and [(("machine learning" OR "artificial intelligence") AND "data mining" AND ("yield prediction" OR "yield forecasting" OR "yield estimation"))](Title, abstract, keywords).

Scopus: The search string is ["machine learning" AND "yield prediction"](Title, abstract, keywords) and [(("machine learning" OR "artificial intelligence") AND "data mining" AND ("yield prediction" OR "yield forecasting" OR "yield estimation"))] (Title, abstract, keywords).

Web of Science: The search string is ["machine learning" AND "yield prediction"] (title, abstract, author keywords, and Keywords Plus).

Springer Link: The search string is ["machine learning" AND "yield prediction"](anywhere) and [(("machine learning" OR "artificial intelligence") AND "data mining" AND ("yield prediction" OR "yield forecasting" OR "yield estimation"))] (anywhere)

Wiley: The search string is ["machine learning" AND "yield prediction"] (anywhere).

Google Scholar: The search string is ["machine learning" AND "yield prediction"] (anywhere) and [(("machine learning" OR "artificial intelligence") AND "data mining" AND ("yield prediction" OR "yield forecasting" OR "yield estimation"))] (anywhere).

For Web of Science and Wiley, the search string [(("machine learning" OR "artificial intelligence") AND "data mining" AND ("yield prediction" OR "yield forecasting" OR "yield estimation"))] did not result in any publications.

3.4. Exclusion criteria

To exclude irrelevant studies, the studies were analyzed and graded based on exclusion criteria to set the boundaries for the systematic review. The exclusion criteria (EC) are shown as follows:

Exclusion criteria 1 - Publication is not related to the agricultural sector and yield prediction combined with machine learning

Table 1
Distribution of papers based on the databases.

Database	# of initially retrieved papers	# of papers after exclusion criteria	Percentage of Papers (%)
Science Direct	17	4	8
Scopus	68	11	22
Web of Science	32	0	0
Springer Link	132	10	20
Wiley	20	1	2
Google Scholar	298	24	48
Total	567	50	100

Exclusion criteria 2 – Publication is not written in English
Exclusion criteria 3 – Publication that is a duplicate or already retrieved from another database
Exclusion criteria 4 – Full text of the publication is not available
Exclusion criteria 5 – Publication is a review/survey paper
Exclusion criteria 6 – Publication has been published before 2008

After the first three exclusion criteria were applied, only 77 studies remained for further analysis. After applying all the six exclusion criteria, 50 studies were selected for further analysis. In Table 1, we show the number of initially retrieved papers and the number of papers after selection criteria were applied. Fig. 4 shows the distribution of selected publications based on the databases we searched. As shown in Table 1, most of the papers were retrieved from Google Scholar, Scopus, and Springer databases.

To answer the four research questions, data from the selected studies have been extracted and synthesized. The information retrieved was focused on checking whether or not the studies meet the requirements stated in the exclusion criteria and on responding to the research questions. The selected studies that passed the exclusion criteria are presented in Appendix A. During the data synthesis, all the extracted data have been combined and synthesized, and the research questions were answered accordingly. The results are presented in Section 4.

4. Results

The selected publications are shown in Table 2. The table shows the publication year, title, and algorithms used in these papers.

Fig. 4 shows the number of publications per year published in the last ten years. This figure indicates that recently the number of papers

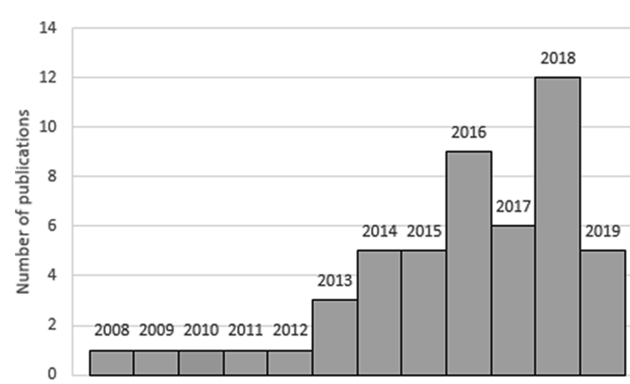

Fig. 4. Distribution of the selected publications per year.

Table 2
Selected publications.

Retrieved From	Reference	Title	Algorithm used	Year
Scopus	Ruß et al. (2008)	Data Mining with Neural Networks for Wheat Yield Prediction	Neural networks	2008
Science Direct	Everingham et al. (2009)	Ensemble data mining approaches to forecast regional sugarcane crop production	Forward stagewise algorithm	2009
Springer Link	Ruß & Kruse (2010)	Regression Models for Spatial Data: An Example from Precision Agriculture	Clustering, random forest, support vector machine	2010
Springer Link	Baral et al. (2011)	Yield Prediction Using Artificial Neural Networks	Neural networks	2011
Springer Link	Črtomir et al. (2012)	Application of Neural Networks and Image Visualization for Early Forecast of Apple Yield	Neural networks	2012
Google Scholar	Johnson (2013)	Crop yield forecasting on the Canadian Prairies by remotely sensed vegetation indices and machine learning methods	Multiple linear regression, neural networks	2013
Google Scholar	Romero et al. (2013)	Using classification algorithms for predicting durum wheat yield in the province of Buenos Aires	K-nearest neighbor, decision tree	2013
Google Scholar	Ananthara et al. (2013)	CRY - an improved crop yield prediction model using bee hive clustering approach for agricultural data sets	Clustering	2013
Scopus	Shekoofa et al. (2014)	Determining the most important physiological and agronomic traits contributing to maize grain yield through machine learning algorithms: A new avenue in intelligent agriculture	Decision tree, clustering	2014
Scopus	Gonzalez-Sanchez et al. (2014)	Predictive ability of machine learning methods for massive crop yield prediction	M5-prime regression tree, k-nearest neighbor, support vector machine	2014
Scopus	Pantazi et al. (2014)	Application of supervised self-organizing models for wheat yield prediction	Neural networks	2014
Google Scholar	Cakir et al. (2014)	Yield prediction of wheat in south-east region of Turkey by using artificial neural networks	Neural networks, multivariate polynomial regression	2014
Google Scholar	Rahman & Haq (2014)	Machine learning facilitated rice prediction in Bangladesh	Decision tree, neural networks, linear regression	2014
Scopus	Kunapuli et al. (2015)	Yield prediction for precision territorial management in maize using spectral data	Polynomial regression, logistic regression	2015
Google Scholar	Matsumura et al. (2015)	Maize yield forecasting by linear regression and artificial neural networks in Jilin, China	Neural networks, multiple linear regression	2015
Google Scholar	Ahamed et al. (2015)	Applying data mining techniques to predict annual yield of major crops and recommend planting different crops in different districts in Bangladesh	Linear regression, neural networks, clustering, k-nearest neighbor	2015
Google Scholar	Paul et al. (2015)	Analysis of soil behavior and prediction of crop yield using data mining approach	Naïve Bayes, k-nearest neighbor	2015
Science Direct	Pantazi et al. (2016)	Wheat yield prediction using machine learning and advanced sensing techniques	Neural networks	2016
Scopus	Jeong et al. (2016)	Random forests for global and regional crop yield predictions	Random forest, linear regression	2016
Wiley	Mola-Yudego et al. (2016)	Spatial yield estimates of fast-growing willow plantations for energy based on climatic variables in northern Europe	Gradient boosting tree	2016
Google Scholar	Everingham et al. (2016)	Accurate prediction of sugarcane yield using a random forest algorithm	Random forest	2016
Scopus	Gandhi et al. (2016)	Rice crop yield prediction in India using support vector machines	Support vector machine	2016
Google Scholar	Bose et al. (2016)	Spiking neural networks for crop yield estimation based on spatiotemporal analysis of image time series	Neural networks	2016
Google Scholar	Gandhi et al. (2016)	Rice crop yield prediction using artificial neural networks	Neural networks	2016
Google Scholar	Gandhi and Armstrong (2016)	Applying data mining techniques to predict yield of rice in Humid Subtropical Climatic Zone of India	Decision tree, logistic regression, k-nearest neighbor	2016
Google Scholar	Sujatha and Isakki (2016)	A study on crop yield forecasting using classification techniques	Naïve Bayes, J48, random forest, neural networks, decision tree, support vector machines *(No experimental results reported)*	2016
Google Scholar	Ying-xue et al. (2017)	Support vector machine-based open crop model (SBOCM): Case of rice production in China	Support vector machine	2017
Google Scholar	Cheng et al. (2017)	Early yield prediction using image analysis of apple fruit and tree canopy features with neural networks	Neural networks	2017
Google Scholar	Bargoti and Underwood (2017)	Image segmentation for fruit detection and yield estimation in apple orchards	Neural networks	2017
Google Scholar	Fernandes et al. (2017)	Sugarcane yield prediction in Brazil using NDVI time series and neural networks ensemble	Neural networks	2017
Google Scholar	You et al. (2017)	Deep Gaussian process for crop yield prediction based on remote sensing data	Neural networks and gaussian process, neural networks	2017
Springer Link	Osman et al. (2017)	Predicting Early Crop Production by Analysing Prior Environment Factors	Neural networks, linear regression	2017
Google Scholar	Ali et al. (2017)	Modeling managed grassland biomass estimation by using multitemporal remote sensing data machine learning approach	ANFIS, neural networks, multiple linear regression	2017
Science Direct	Kouadio et al. (2018)	Artificial intelligence approach for the prediction of Robusta coffee yield using soil fertility properties	Extreme learning machine, multiple linear regression, random forest	2018
Springer Link	Goldstein et al. (2018)	Applying machine learning on sensor data for irrigation recommendations: revealing the agronomists tacit knowledge	Gradient boosting tree, linear regression	2018
Scopus	Zhong et al. (2018)	Hierarchical modeling of seed variety yields and decision making for future planting plan	Random forest, linear regression	2018
Scopus	Crane-Droesch (2018)	Machine learning methods for crop yield prediction and climate change impact assessment in agriculture	Neural networks	2018
Scopus	Villanueva et al. (2018)	Bitter melon crop yield prediction using Machine Learning Algorithm	Neural networks	2018
Google Scholar	Girish et al. (2018)	Crop Yield and Rainfall Prediction in Tumakuru District using Machine Learning	Support vector machine, linear regression, k-nearest neighbor	2018
Google Scholar	Khanal et al. (2018)	Integration of high resolution remotely sensed data and machine learning techniques for spatial prediction of soil properties and corn yield	Neural networks, support vector machine, random forest	2018
Google Scholar	Taherei Ghazvinei et al. (2018)	Sugarcane growth prediction based on meteorological parameters using extreme learning machine and artificial neural network	Neural networks	2018
Springer Link	Ahmad et al. (2018)	Yield Forecasting of Spring Maize Using Remote Sensing and Crop Modeling in Faisalabad-Punjab Pakistan	Support vector machine, random forest, decision tree	2018

(*continued on next page*)

Table 2 (*continued*)

Retrieved From	Reference	Title	Algorithm used	Year
Springer Link	Shah et al. (2018)	Smart Farming System: Crop Yield Prediction Using Regression Techniques	Support vector machine, random forest, multivariate polynomial regression	2018
Springer Link	Monga (2018)	Estimating Vineyard Grape Yield from Images	Neural networks	2018
Google Scholar	Wang et al. (2018)	Deep transfer learning for crop yield prediction with remote sensing data	Neural networks	2018
Science Direct	Xu et al. (2019)	Design of an integrated climatic assessment indicator (ICAI) for wheat production: A case study in Jiangsu Province, China	Random forest, support vector machine	2019
Scopus	Filippi et al. (2019b)	An approach to forecast grain crop yield using multi-layered, multi-farm data sets and machine learning	Random forest	2019
Google Scholar	Rao & Manasa (2019)	Artificial Neural Networks for Soil Quality and Crop Yield Prediction using Machine Learning	Neural networks	2019
Springer Link	Ranjan & Parida (2019)	Paddy acreage mapping and yield prediction using sentinel-based optical and SAR data in Sahibganj district, Jharkhand (India)	Linear regression	2019
Springer Link	Charoen-Ung & Mittrapiyanuruk (2019)	Sugarcane Yield Grade Prediction Using Random Forest with Forward Feature Selection and Hyper-parameter Tuning	Random forest	2019

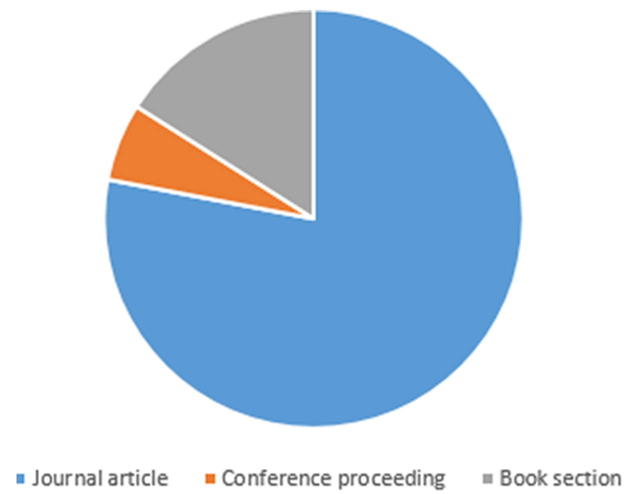

Fig. 5. Distribution of the type of 50 primary publications.

on crop yield prediction is increasing.

There were no exclusion criteria based on the type of publication; therefore, conference papers were also included. The pie chart in Fig. 5 shows the distribution of types of publications. The figure shows that most of the articles we accessed are journal articles; conference papers and book chapters constitute less than 25% of the total number of papers.

To address research question two (RQ2), features used in the machine learning algorithms applied in the papers were investigated and summarized. All features we were able to extract are shown in Table 3.

As shown in Table 3, the most used features are related to temperature, rainfall, and soil type. Crop yield is the dependent variable. To get a better overview of the independent variables (features), the features were grouped. The independent features can be grouped into soil and crop information, humidity, nutrients, and field management. The number of times these groups are used is presented in Table 4. As shown in this table, the feature groups that are most used are related to the soil, solar, and humidity information.

The feature group "soil information" consists of the following variables: soil maps, soil type, pH value, cation exchange capacity, and area of production. Whether or not soil maps were used and the information content of the maps differs among the different publications. In the soil maps, general information about the nutrients in the soil, type of the soil, and location can be found. Crop information refers to information about the crop itself, such as weight, growth during the growth-process, variety of plants, and crop density. Other measurements that indicate growth is also included in this group, for example, the leaf area index. Humidity stands for the water in the field. The features that fall under the humidity group include rainfall, humidity, forecasted rainfall, and precipitation. Nutrients can be nutrients that are already in the soil, but the nutrients can also be applied nutrients. These features measure the level of saturation. The measured nutrients are nitrogen, magnesium, potassium, sulphur, zinc, boron, calcium, manganese, and phosphorus. With field management, decisions of farmers to adjust their field are grouped. These features are irrigation and fertilization, and thus field management could also refer to the management of nutrients. The solar information contains features related to radiation or temperature. These are gamma radiometric, temperature, photoperiod, shortwave radiation, degree-days, and solar radiation. The feature group labeled as 'Other' contains the features that cannot be put in any of the groups mentioned above. Most of these features are used only once or are calculated features (Measuring Vegetation (NDVI & EVI), 2000). These features are used less and include features such as wind speed, pressure, and images. The calculated features are MODIS Enhanced Vegetation Index (MODIS-EVI), Normalized Vegetation Index (NDVI), and Enhanced Vegetation Index

Table 3
All features used.

Feature	# of times used
Temperature	24
Soil type	17
Rainfall	17
Crop information	13
Soil maps	12
Humidity	11
pH-value	11
Solar radiation	10
Precipitation	9
Images	8
Area of production	8
Fertilization	7
NDVI	6
Cation exchange capacity	6
Nitrogen	6
Irrigation	5
Potassium	5
Wind speed	5
Zinc	3
Magnesium	3
Shortwave radiation	2
Sulphur	2
Boron	2
Calcium	2
Organic carbon	2
EVI	2
Phosphorus	2
Gamma radiametrics	1
MODIS-EVI	1
Forecasted rainfall	1
Photoperiod	1
Climate	1
Degree-days	1
Time	1
Pressure	1
Leaf area index	1
Manganese	1

Table 4
Grouped features.

Group	# of times used
Soil information	54
Solar information	39
Humidity	38
Nutrients	28
Other	24
Crop information	14
Field management	12

(EVI) (Filippi et al., 2019a).

To represent all the features gathered through this SLR study, we drew a feature map depicted in Fig. 6 shows the significant features and sub-features.

To address the first research question (RQ1), machine learning algorithms were investigated and summarized. The algorithms used more than once are listed in Table 5. As shown in the table, Neural Networks (NN) and Linear Regression algorithms are the two algorithms used mostly. Also, Random Forest (RF) and Support Vector Machines (SVM) are widely used, according to Table 5.

To address research question three (RQ3), evaluation parameters were identified. All the evaluation parameters that were used and the number of times they were used are shown in Table 6. As the table shows, Root Mean Square Error (RMSE) is the most used parameter in the studies.

Apart from the evaluation parameters, several validation approaches were used as well. Most of the time, cross-validation is used. The most used evaluation method was 10-fold cross-validation.

To address research question four (RQ4), the publications were read to see if they stated any problems or improvements for future models. In several studies, insufficient availability of data (too few data) was mentioned as a problem. The studies stated that their systems worked for the limited data that they had at hand, and indicated data with more variety should be used for further testing. This means data with different climatic circumstances, different vegetation, and longer time-series of yield data. Another suggested improvement is that more data sources should be integrated. Finally, the publication indicated that the use of machine learning in farm management systems should be explored. If the models work as requested, software applications must be created that allow the farmer to make decisions based on the models.

5. Deep learning-based crop yield prediction

In the first part of our research (i.e., Systematic Literature Review), we observed that Artificial Neural Networks (ANN) is the most used algorithm for crop yield prediction. Recently, deep learning, which is a sub-branch of machine learning, has provided state-of-the-art results in many different domains, such as face recognition and image classification. These Deep Neural Networks (DNN) algorithms use similar concepts of ANN algorithms; however, they include different hidden layer types such as convolutional layer and pooling layer and consist of many hidden layers instead of a single hidden layer.

As such, in the second part of our research, we aimed to investigate to what extent deep learning algorithms have been applied in crop yield prediction. To broaden our analysis and reach recent applications of deep learning algorithms in yield prediction, we designed a new search criterion (i.e., “deep learning” AND “yield prediction”) and performed a new search in the same electronic databases that were used during the SLR study. We reached the following 30 papers shown in Table 7. We investigated these articles in detail, extracted, and synthesized the deep learning algorithms applied by researchers.

Fig. 7 shows the yearly distribution of deep learning-based papers. Although we are in the half of the year 2020, the number of papers that belong to the year 2020 is now equal to the number of papers published in 2019. This shows that the number of papers is increasing every year.

In Table 8, we show the distribution of deep learning-based papers per database. Most of the papers were retrieved from Google Scholar, and the second top database was Scopus. Science Direct and Springer Link returned a similar number of deep learning-based papers.

In Table 9, we show the distribution of applied deep learning algorithms in the identified papers list. The most applied deep learning algorithm is Convolutional Neural Networks (CNN), and the other widely used algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN) algorithms. Since some papers applied more than one deep learning algorithm, the total number of usages shown in the second column is larger than the total number of papers.

These deep learning algorithms are shortly described as follows:

- *Deep Neural Networks (DNN):* These DNN algorithms are very similar to the traditional Artificial Neural Networks (ANN) algorithms except the number of hidden layers. In DNN networks, there are many hidden layers that are mostly fully connected, as in the case of ANN algorithms. However, for other kinds of deep learning algorithms such as CNN, there are also different types of layers, such as the convolutional layer and the pooling layer.
- *Convolutional Neural Networks (CNN):* Compared to a fully connected network, CNN has fewer parameters to learn. There are three types of layers in a CNN model, namely convolutional layers, pooling layers, and fully-connected layers. Convolutional layers consist of filters and feature maps. Filters are the neurons of the layer, have weighted inputs, and create an output value (Brownlee, 2016). A feature map can be considered as the output of one filter. Pooling layers are applied to down-sample the feature map of the previous layers, generalize feature representations, and reduce the

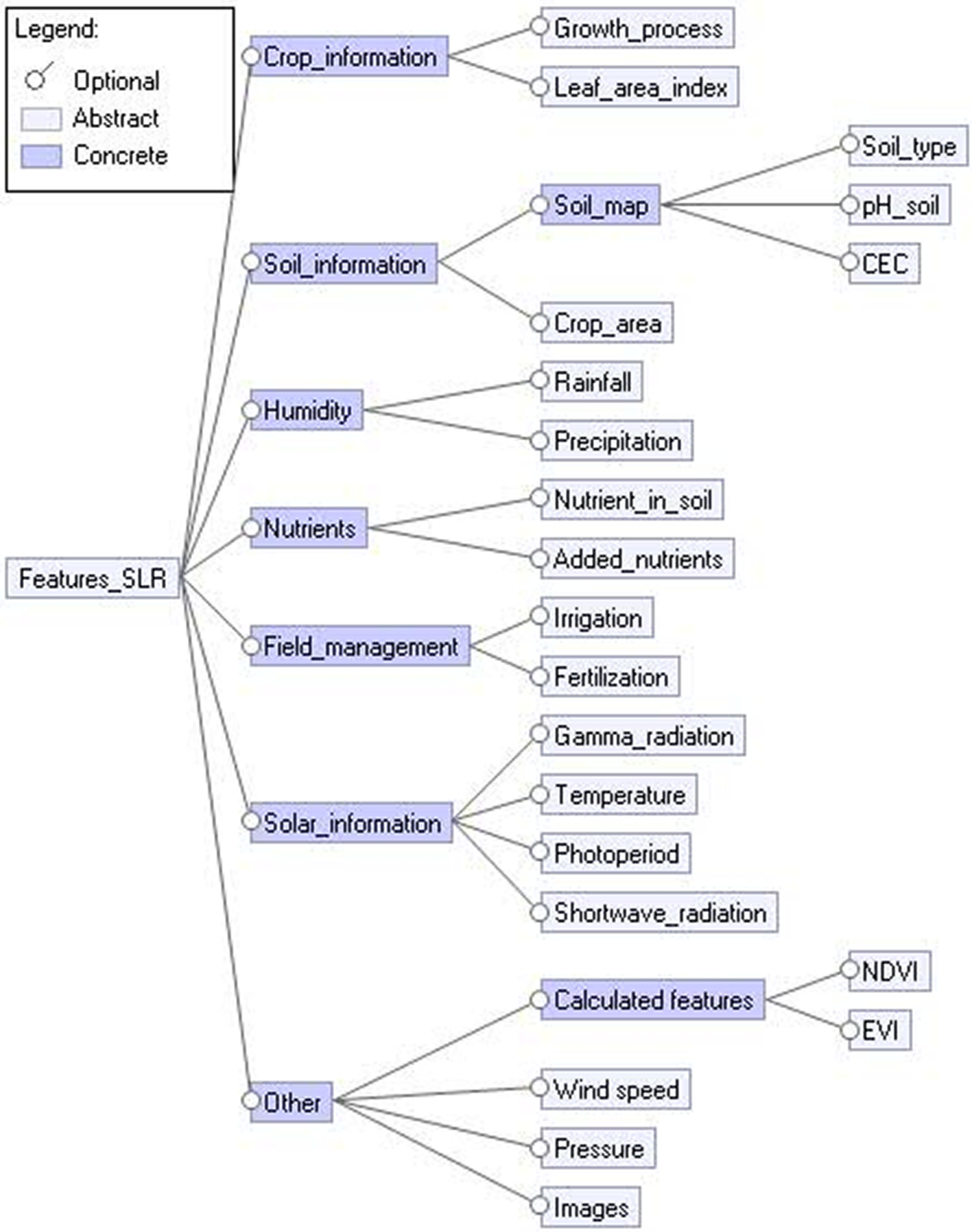

Fig. 6. Feature diagram.

Table 5
Most used machine learning algorithms.

Most used machine learning algorithms	# of times used
Neural Networks	27
Linear Regression	14
Random Forest	12
Support Vector Machine	10
Gradient Boosting Tree	4

overfitting (Brownlee, 2019). Fully-connected layers are mostly used at the end of the network for predictions. The general pattern for CNN models is that one or more convolutional layers are followed by a pooling layer, and this structure is repeated several times, and finally, fully connected layers are applied (Brownlee, 2016, 2019).

- *Long-Short Term Memory (LSTM):* LSTM networks were designed specifically for sequence prediction problems. There are several LSTM architectures (Brownlee, 2017), namely vanilla LSTM, stacked LSTM, CNN-LSTM, Encoder-Decoder LSTM, Bidirectional LSTM, and Generative LSTM. There are several limitations of Multi-Layer

Table 6
All evaluation parameters used.

Key	Evaluation parameter	# of times used
RMSE	Root mean square error	29
R^2	R-squared	19
MAE	Mean absolute error	8
MSE	Mean square error	5
MAPE	Mean absolute percentage error	3
RSAE	Reduced simple average ensemble	3
LCCC	Lin's concordance correlation coefficient	1
MFE	Multi factored evaluation	1
SAE	Simple average ensemble	1
rcv	Reference change values	1
MCC	Matthew's correlation coefficient	1

Table 7
Deep learning-based publications.

Retrieved From	Reference	Title	Deep Learning Algorithm(s) used	Year
Science Direct	Schwalbert et al. (2020)	Satellite-based soybean yield forecast: Integrating machine learning and weather data for improving crop yield prediction in southern Brazil	Long-Short Term Memory (LSTM)	2020
Science Direct	Chu and Yu (2020)	An end-to-end model for rice yield prediction using deep learning fusion	The combination of Back-Propagation Neural Networks (BPNNs) and Independently Recurrent Neural Network (IndRNN)	2020
Science Direct	Tedesco-Oliveira et al. (2020)	Convolutional neural networks in predicting cotton yield from images of commercial fields	Convolutional Neural Networks (CNN)	2020
Science Direct	Nevavuori et al. (2019)	Crop yield prediction with deep convolutional neural networks	Convolutional Neural Networks (CNN)	2019
Science Direct	Maimaitijiang et al. (2020)	Soybean yield prediction from UAV using multimodal data fusion and deep learning	Deep Neural Networks (DNN)	2020
Science Direct	Yang et al. (2019)	Deep convolutional neural networks for rice grain yield estimation at the ripening stage using UAV-based remotely sensed images	Convolutional Neural Networks (CNN)	2019
Google Scholar	Khaki and Wang (2019)	Crop Yield Prediction Using Deep Neural Networks	Deep Neural Networks (DNN)	2019
Google Scholar	Rahnemoonfar and Sheppard (2017)	Real-time yield estimation based on deep learning	Convolutional Neural Networks (CNN)	2017
Google Scholar	Chen et al. (2019)	Strawberry Yield Prediction Based on a Deep Neural Network Using High-Resolution Aerial Orthoimages	Faster Region-based Convolutional Neural Networks (Faster R-CNN)	2019
Google Scholar	Sun et al. (2019)	County-Level Soybean Yield Prediction Using Deep CNN-LSTM Model	The combination of Convolutional Neural Networks and Long-Short Term Memory Networks (CNN-LSTM)	2019
Google Scholar	Khaki et al. (2020)	A CNN-RNN Framework for Crop Yield Prediction	The combination of Convolutional Neural Networks and Recurrent Neural Networks (CNN-RNN)	2020
Google Scholar	Terliksiz and Altýlar (2019)	Use Of Deep Neural Networks For Crop Yield Prediction: A Case Study Of Soybean Yield in Lauderdale County, Alabama, USA	3D Convolutional Neural Networks (3D CNN)	2019
Google Scholar	Lee et al. (2019)	A Self-Predictable Crop Yield Platform (SCYP) Based On Crop Diseases Using Deep Learning	Convolutional Neural Networks (CNN)	2019
Google Scholar	Elavarasan and Vincent (2020)	Crop Yield Prediction Using Deep Reinforcement Learning Model for Sustainable Agrarian Applications	Deep Recurrent Q-Network	2020
Google Scholar	Wang et al. (2020)	Winter Wheat Yield Prediction at County Level and Uncertainty Analysis in Main Wheat-Producing Regions of China with Deep Learning Approaches	The combination of Convolutional Neural Networks and Long-Short Term Memory (CNN-LSTM)	2020
Google Scholar	Wolanin et al. (2020)	Estimating and understanding crop yields with explainable deeplearning in the Indian Wheat Belt	Convolutional Neural Networks (CNN)	2020
Springer Link	Bhojani and Bhatt (2020)	Wheat crop yield prediction using new activation functions in neuralnetwork	Deep Neural Networks (DNN)	2020
Springer Link	Fathi et al. (2019)	Crop Yield Prediction Using Deep Learning in Mediterranean Region	Deep Neural Networks (DNN)	2019
Springer Link	Shidnal et al. (2019)	Crop yield prediction: two-tiered machine learning model approach	Convolutional Neural Networks (CNN)	2019
Springer Link	Khaki and Wang (2019)	Crop Yield Prediction Using Deep Neural Networks	Deep Neural Networks (DNN)	2019
Springer Link	Nguyen et al. (2019)	Spatial-Temporal Multi-Task Learningfor Within-Field Cotton Yield Prediction	Spatial-Temporal Multi-Task Learning	2019
Springer Link	De Alwis et al. (2019)	Duo Attention with Deep Learning on Tomato Yield Prediction and Factor Interpretation	Duo Attention Long-Short Term Memory	2019
Wiley	Jiang et al. (2020)	A deep learning approach to conflating heterogeneous geospatial data for corn yield estimation: A case study of the US Corn Belt at the county level	Long-Short Term Memory (LSTM)	2020
Scopus	Saravi et al. (2019)	Quantitative model of irrigation effect on maize yield by deep neural network	Deep Neural Networks (DNN)	2019
Scopus	Zhang et al. (2020)	Combining Optical, Fluorescence, Thermal Satellite, and Environmental Data to Predict County-Level Maize Yield in China Using Machine Learning Approaches	Long-Short Term Memory (LSTM)	2020
Scopus	Kang et al. (2020)	Comparative assessment of environmental variables and machine learning algorithms for maize yield prediction in the US Midwest	Long-Short Term Memory (LSTM) and Convolutional Neural Networks (CNN)	2020
Scopus	Wang et al. (2020)	Combining Multi-Source Data and Machine Learning Approaches to Predict Winter Wheat Yield in the Conterminous United States	Deep Neural Networks (DNN)	2020
Scopus	Ju et al. (2020)	Machine learning approaches for crop yield prediction with MODIS and weather data	Long-Short Term Memory (LSTM) Convolutional Neural Networks (CNN), Stacked-Sparse AutoEncoder (SSAE)	2020
Scopus	Yalcin (2019)	An Approximation for A Relative Crop Yield Estimate from Field Images Using Deep Learning	Convolutional Neural Networks (CNN)	2019
Scopus	Wang et al. (2018)	Deep Transfer Learning for Crop Yield Prediction with Remote Sensing Data	Long-Short Term Memory (LSTM) for Transfer Learning	2018

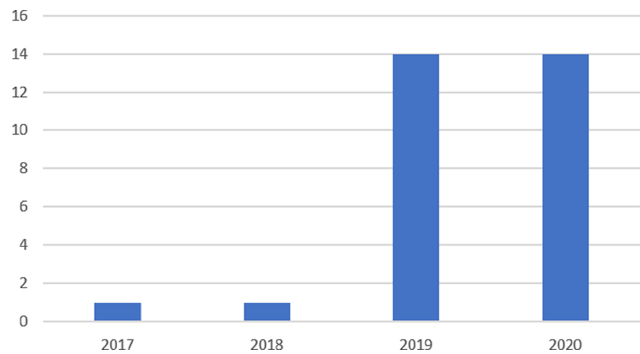

Fig. 7. Yearly distribution of deep learning-based papers.

Table 8
Distribution of deep learning-based papers per database.

Database	# of papers	Percentage of Papers (%)
Science Direct	6	20
Scopus	7	23,33
Web of Science	0	0
Springer Link	6	20
Wiley	1	3,33
Google Scholar	10	33,33
Total	30	100

Table 9
Distribution of deep learning algorithms.

Algorithms used	# of usages	Percentage (%)
CNN	10	30,30
LSTM	7	21,21
DNN	7	21,21
Hybrid	4	12,12
Autoencoder	1	3,03
Multi-Task Learning (MTL)	1	3,03
Deep Recurrent Q-Network (DQN)	1	3,03
3D CNN	1	3,03
Faster R-CNN	1	3,03
Total	33	100

Perceptron (MLP) feedforward ANN algorithms, such as being stateless, unaware of temporal structure, messy scaling, fixed sized inputs, and fixed-sized outputs (Brownlee, 2017). Compared to the MLP network, LSTM can be considered as the addition of loops to the network. Also, LSTM is a special type of Recurrent Neural Network (RNN) algorithm. Since LSTM has an internal state, is aware of the temporal structure in the inputs, can model parallel input series, can process variable-length input to generate variable-length output, they are very different than the MLP networks. The memory cell is the computational unit of the LSTM (Brownlee, 2017). These cells consist of weights (i.e., input weights, output weights, and internal state) and gates (i.e., forget gate, input gate, and output gate).

- *3D CNN:* This network is a special type of CNN model in which the kernels move through height, length, and depth. As such, it produces 3D activation maps. This type of model was developed to improve the identification of moving, as in the case of security cameras and medical scans. 3D convolutions are performed in the convolutional layers of CNN (Ji et al., 2012).
- *Faster R-CNN:* The Region-Based Convolutional Neural Network (R-CNN) is a family of CNN models that were designed specifically for object detection (Brownlee, 2019). There are four variations of R-CNN, namely R-CNN, Fast R-CNN, Faster R-CNN, and Mask R-CNN. In Faster R-CNN, a Region Proposal Network is added to interpret features extracted from CNN (Ren et al., 2015).
- *Autoencoder:* Autoencoders are unsupervised learning approaches that consist of the following four main parts: encoder, bottleneck, decoder, and reconstruction loss. The architecture of autoencoders can be designed based on simple feedforward neural networks, CNN, or LSTM networks (Baldi, 2012; Vincent et al., 2008).
- *Hybrid networks:* It is possible to combine the power of different deep learning algorithms. As such, researchers combine different algorithms in a different way. Chu and Yu (2020) combined Back-Propagation Neural Networks (BPNNs) and Independently Recurrent Neural Network (IndRNN) and applied this model for crop yield prediction. Sun et al. (2019) combined Convolutional Neural Networks and Long-Short Term Memory Networks (CNN-LSTM) for soybean yield prediction. Khaki et al. (2020) combined Convolutional Neural Networks and Recurrent Neural Networks (CNN-RNN) for yield prediction. Wang et al. (2020) combined CNN and LSTM (CNN-LSTM) networks for the wheat yield prediction problem.
- *Multi-Task Learning (MTL):* In multi-task learning, we share representations between tasks to improve the performance of our models developed for these tasks (Ruder, 2017). It has been applied in many different domains, such as drug discovery, speech recognition, and natural language processing. The aim is to improve the performance of all the tasks involved instead of improving the performance of a single task. Zhang and Yang (2017) reviewed several multi-task learning approaches for supervised learning tasks and also explained how to combine multi-task learning with other learning categories, such as semi-supervised learning and reinforcement learning. They divided supervised MTL approaches into the following categories: feature learning approach, low-rank approach, task clustering approach, task relation learning approach, and decomposition approach.
- *Deep Recurrent Q-Network (DQN):* In reinforcement learning, agents observe the environment and act based on some rules and the available data. Agents get rewards based on their actions (i.e., positive or negative reward) and try to maximize this reward. The environment and agents interact with each other continuously. DQN algorithm was developed in 2015 by the researchers of DeepMind acquired by Google in 2014. This DQN algorithm that combines the power of reinforcement learning and deep neural networks solved several Atari games in 2015. The classical Q-learning algorithm was enhanced with deep neural networks, and also, the experience replay technique was integrated (Mnih et al., 2015). Elavarasan and Vincent (2020) applied this algorithm for crop yield prediction.

The number of papers that apply deep learning for crop yield prediction is increasing. As such, we expect to see more research in this direction.

6. Discussion

- **General discussion:** Such research is susceptible to threats to validity, and potential threats to validity can be external, construct validity, and reliability (Šmite et al., 2010). The external validity and construct validity are addressed for this SLR study since the initial search string was broad, and the query returned a substantial number of studies: 567 publications in total. The search string covered the whole scope of the SLR. For reliability of the SLR, the validity can be considered well-addressed since the process of the SLR has been described clearly and is replicable. If this SLR is replicated, it could return slightly different selected publications, but the differences would be a result of different personal judgments. However, it is highly unlikely that the overall findings would change.
- **Search-related discussion:** There is a possibility that valuable publications might have been missed. More synonyms could have been used, and a broader search could have returned new studies. However, the search string resulted in a high number of publications

indicating a broad enough search.

- **Analysis-related discussion:** Another issue that could be a threat to validity the way the analysis is conducted. For example, not all publications stated what kind of evaluation parameters were used, and sometimes just a few examples of features were explained. Thus, sometimes this information that is required to address the research questions could not be found in the paper. This way, the data that was used to answer the research questions were derived from a few numbers of publications than a total of 50 selected publications. To get more information about the publications, the authors could potentially have been contacted, but this line of action was not feasible within the context of this research, and that might also not solve all the issues.
- **RQ1-Related (algorithms) discussion:** Linear Regression is the second most used algorithms, according to Table 5. Linear Regression is used as a benchmarking algorithm in most cases to check whether the proposed algorithm is better than Linear Regression or not. Therefore, although it is shown in many articles, it does not mean that it is the best performing algorithm. Table 5 should be interpreted carefully because "most used" does not mean the best-performing ones. In fact, Deep Learning (DL), which is a sub-branch of Machine Learning, has been used for the crop yield prediction problem recently and is believed to be very promising. In this study, we also identified several deep learning-based studies. There are several additional promising aspects of DL methods, such as automatic feature extraction and superior performance. We expect that more research will be conducted on the use of DL approaches in crop yield prediction in the near future due to the superior performance of DL algorithms in other problem domains.

Among the selected publications, both classifiers and clustering algorithms are used. Since pictures are used for clustering in those publications, the publication is in connection with the machine vision instead of ML using a numerical dataset. The use of clustering algorithms for this problem can be investigated in detail to find different research perspectives in this problem.

- **RQ2-related (features) discussion:** Groups are created for features and algorithms to visualize the main features and algorithms. Due to this decision, detailed information is lost, but clarity has been maintained. The most used features are soil type, rainfall, and temperature. Apart from those features that are used in several studies, there are also features that were used in specific studies. Those features are gamma radiation, MODIS-EVI, forecast rainfall, humidity, photoperiod, pH-value, irrigation, leaf area, NDVI, EVI, and crop information. There are also studies that use different nutrients as features, which are magnesium, potassium, sulphur, zinc, nitrogen, boron, and calcium. The most used features are not always the same kind of data. Temperature, for example, is measured as average temperature, but more features like maximum temperature and minimum temperature are also applied.
- **RQ3-related (evaluation parameters and approaches) discussion:** There are not many evaluation parameters reported in the selected papers. Almost every study used RMSE as the measurement of the quality of the model. Other evaluation parameters are MSE, R^2, and MAE. Some parameters were used in specific studies, most of these parameters look like some of the previously mentioned parameters, with a small difference. These are MAPE, LCCC, MFE, SAE, rcv, RSAE, and MCC. Most of the models had outcomes with high accuracy values for their evaluation parameters, which means that the model made correct predictions. As the evaluation approach, the 10-fold cross-validation approach was preferred by researchers.
- **RQ4-related (challenges) discussion:** Challenges were reported based on the explicit statements in the articles. However, there might be additional challenges that were not stated in the identified papers. The challenges are mainly in the field of improvement of a working model. When more data is gathered to train and test, much more can be said about the precision of the model. Another challenge is the implementation of the models into the farm management systems. When applications are made that the farmer can use, then only can the models be useful to make decisions, also during the growing season. When specific parameters for that specific place are measured and added, predictions will have higher precision.

7. Conclusion

This study showed that the selected publications use a variety of features, depending on the scope of the research and the availability of data. Every paper investigates yield prediction with machine learning but differs from the features. The studies also differ in scale, geological position, and crop. The choice of features is dependent on the availability of the dataset and the aim of the research. Studies also stated that models with more features did not always provide the best performance for the yield prediction. To find the best performing model, models with more and fewer features should be tested. Many algorithms have been used in different studies. The results show that no specific conclusion can be drawn as to what the best model is, but they clearly show that some machine learning models are used more than the others. The most used models are the random forest, neural networks, linear regression, and gradient boosting tree. Most of the studies used a variety of machine learning models to test which model had the best prediction.

Since Neural Networks is the most applied algorithm, we also aimed to investigate to what extent deep learning algorithms were used for crop yield prediction. After the identification of 30 papers that applied deep learning, we extracted and synthesized the applied algorithms. We observed that CNN, LSTM, and DNN algorithms are the most preferred deep learning algorithms. However, there are also other kinds of algorithms applied to this problem. We consider that this article will pave the way for further research on the development of crop yield prediction problem.

In our future work, we aim to build on the outcomes of this study and focus on the development of a DL-based crop yield prediction model.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

In Table A1, features used per publications are shown. If there is a '1' in the box, it means that that specific feature was used.

In Table A2, the evaluation parameters used per publication are presented.

Table A1
Features used per selected publication.

Paper	Soil type	Gamma radia-metrics	Soil maps	MODIS-EVI	Rainfall	Forecas-ted rainfall	Precipi-tation	Temper-ature	Humidi-ty	Photop-eriod	Fertiliz-ation	Climate	pH-value	Irrigati-on	Cation ex-change capacity	Magnes-ium	Potassi-um	Area of produc-tion	Wind Speed
Filippi et al., 2019	1	1	1	1	1	1													
Jeong et al., 2016	1		1		1				1	1	1	1							
Zhong et al., 2018	1				1			1					1						
Villanueva and Salenga, 2018																			
Crane-Droesch, 2018	1		1		1			1	1					1					1
Gonzalez-Sanchez et al., 2014	1		1		1			1						1					
Xu et al., 2019							1	1											1
Pantazi et al., 2016	1		1										1						
Kouadio et al., 2018	1		1										1			1	1		
Kunapuli et al., 2015											1							1	
Shekoofa et al., 2014	1										1								
Pantazi et al., 2014			1										1		1	1			
Goldstein et al., 2018	1							1	1										
Mola-Yudego et al., 2016							1	1											
Girish et al., 2018					1														
Rao and Manasa, 2019	1		1					1			1		1				1		
Khanal et al., 2018	1		1										1		1	1	1		
Cheng et al., 2017																			
Everingham et al., 2009					1			1											
Everingham et al., 2016					1			1											
Bargoti and Underwood, 2017																			
Fernandes and Ebecken, 2017								1											
Johnson et al., 2013																			
Matsumura et al., 2015							1	1			1								
Taherei Ghazvinei, 2018					1			1	1					1	1				

(*continued on next page*)

Table A1 (*continued*)

Paper	Soil type	Gamma radia-metrics	Soil maps	MODIS-EVI	Rainfall	Forecas-ted rainfall	Precipi-tation	Temper-ature	Humidi-ty	Photop-eriod	Fertiliz-ation	Climate	pH-value	Irrigati-on	Cation ex-change capacity	Magnes-ium	Potassi-um	Area of produc-tion	Wind Speed
Romero et al., 2013																			
Su et al., 2017	1		1				1	1	1				1				1		1
You et al., 2017																			
Ahmad et al., 2018	1														1				
Črtomir et al., 2012																			
Osman et al., 2017					1			1	1									1	1
Ranjan and Parida, 2019			1															1	
Shah et al., 2018					1			1	1										
Russ et al., 2008											1				1				
Monga, 2018																			
Russ and Kruse, 2010			1								1				1				
Baral et al., 2011					1		1	1											
Ahamed et al., 2015					1			1	1				1	1				1	
Ali et al., 2017							1	1											
Cakir et al., 2014					1			1	1										1
Gandhi et al., 2016							1	1										1	
Wang et al., 2018																			
Charoen-Ung and Mittrapiyanuruk, 2019	1				1									1				1	
Ananthara et al., 2013	1				1				1				1						
Bose et al., 2016								1											
Gandhi et al., 2016							1	1										1	
Gandhi and Armstrong, 2016	1						1	1										1	
Paul et al., 2015													1				1		
Rahman and Haq, 2014					1			1	1										
Sujatha and Isakki, 2016	1												1						

Paper	Shortw-ave radia-tion	Degree-days	Time	Solar radia-tion	Pressure	Sulphur	Zinc	Nitroge-n	Boron	Calcium	Crop Inform-ation	Leaf Area Index	Phosph-orus	Manga-nese	Organic carbon	Images	NDVI	EVI
Filippi et al., 2019																		
Jeong et al., 2016																		
Zhong et al., 2018				1														
Villanueva and Salenga, 2018																		
Crane-Droesch, 2018	1	1	1															

(*continued on next page*)

Table A1 (*continued*)

Paper	Shortwave radiation	Degree-days	Time	Solar radiation	Pressure	Sulphur	Zinc	Nitrogen	Boron	Calcium	Crop Information	Leaf Area Index	Phosphorus	Manganese	Organic carbon	Images	NDVI	EVI
Gonzalez-Sanchez et al., 2014				1														
Xu et al., 2019				1														
Pantazi et al., 2016																		
Kouadio et al., 2018						1	1	1	1	1								
Kunapuli et al., 2015											1	1						
Shekoofa et al., 2014											1							
Pantazi et al., 2014								1		1					1			
Goldstein et al., 2018				1							1							
Mola-Yudego et al., 2016																		
Girish et al., 2018																		
Rao and Manasa, 2019							1	1	1		1		1	1				
Khanal et al., 2018																		
Cheng et al., 2017											1							
Everingham et al., 2009				1														
Everingham et al., 2016				1	1													
Bargoti and Underwood, 2017																1		
Fernandes and Ebecken, 2017																	1	
Johnson et al., 2013																	1	1
Matsumura et al., 2015																		
Taherei Ghazvinei, 2018	1																	
Romero et al., 2013											1							
Su et al., 2017													1					

(*continued on next page*)

Table A1 (*continued*)

Paper	Shortwave radiation	Degree-days	Time	Solar radiation	Pressure	Sulphur	Zinc	Nitrogen	Boron	Calcium	Crop Information	Leaf Area Index	Phosphorus	Manganese	Organic carbon	Images	NDVI	EVI
You et al., 2017																1		
Ahmad et al., 2018								1			1				1	1	1	
Črtomir et al., 2012																1		
Osman et al., 2017											1							
Ranjan and Parida, 2019											1							
Shah et al., 2018																		
Russ et al., 2008								1										
Monga, 2018																1		
Russ and Kruse, 2010																		
Baral et al., 2011																		
Ahamed et al., 2015				1														
Ali et al., 2017																1	1	1
Cakir et al., 2014				1														
Gandhi et al., 2016											1							
Wang et al., 2018																1	1	
Charoen-Ung and Mittrapiyanuruk, 2019																		
Ananthara et al., 2013				1							1							
Bose et al., 2016																1	1	
Gandhi et al., 2016											1							
Gandhi and Armstrong, 2016																		
Paul et al., 2015						1	1	1										
Rahman and Haq, 2014				1														
Sujatha and Isakki, 2016											1							

Table A2
Evaluation parameters used per publication.

Paper	Root mean square error	Lin's concordance correlation coefficient	Mean square error	R-squared	Mean absolute error	Mean absolute percentage error	Multi factored evaluation	Simple average ensemble	Reference change values	Reduced simple average ensemble	Matthew's correla-tion coefficient
Filippi et al., 2019	1	1	1								
Jeong et al., 2016	1										
Zhong et al., 2018	1				1						
Villanueva and Salenga, 2018											
Crane-Droesch, 2018			1								
Gonzalez-Sanchez et al., 2014	1			1	1						
Xu et al., 2019	1			1							
Pantazi et al., 2016	1										
Kouadio et al., 2018	1				1						
Kunapuli et al., 2015				1							
Shekoofa et al., 2014											
Pantazi et al., 2014											
Goldstein et al., 2018	1										
Mola-Yudego et al., 2016	1			1							
Girish et al., 2018											
Rao and Manasa, 2019											
Khanal et al., 2018	1			1							
Cheng et al., 2017	1			1		1	1				
Everingham et al., 2009								1	1	1	
Everingham et al., 2016				1							
Bargoti and Underwood, 2017				1							
Fernandes and Ebecken, 2017	1			1							
Johnson et al., 2013											
Matsumura et al., 2015	1		1								
Taherei Ghazvinei, 2018	1			1							
Romero et al., 2013											
Su et al., 2017	1										
You et al., 2017	1										
Ahmad et al., 2018	1			1	1	1					
Črtomir et al., 2012				1							

(continued on next page)

Table A2 (*continued*)

Paper	Root mean square error	Lin's concordance correlation coefficient	Mean square error	R-squared	Mean absolute error	Mean absolute percentage error	Multi factored evaluation	Simple average ensemble	Reference change values	Reduced simple average ensemble	Matthew's correla-tion coefficient
Osman et al., 2017	1										
Ranjan and Parida, 2019											
Shah et al., 2018	1			1	1						
Russ et al., 2008			1	1							
Monga, 2018				1	1						
Russ and Kruse, 2010	1										
Baral et al., 2011											
Ahamed et al., 2015	1										
Ali et al., 2017	1			1							
Cakir et al., 2014	1										
Gandhi et al., 2016	1			1	1					1	
Wang et al., 2018	1			1							
Charoen-Ung and Mittrapiyanuruk, 2019											
Ananthara et al., 2013											
Bose et al., 2016	1		1			1					
Gandhi et al., 2016	1			1							1
Gandhi and Armstrong, 2016	1				1					1	
Paul et al., 2015											
Rahman and Haq, 2014	1										
Sujatha and Isakki, 2016											

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2020.105709.

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