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Review Article

Review of machine learning and deep learning models in agriculture

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ABSTRACT

Machine learning (ML) refers to the processes that enable computers to think based on various learning methods. It can be also called domain which is a subset of Artificial Intelligence (AI). Deep learning (DL) has been a promising, new and modern technique for data analysis in recent years. It can be shown as the improved version of Artificial Neural Networks (ANN) which is one of the popular AI methods of today. The population of the world is increasing day by day and the importance of agriculture is also increasing in parallel. Because of this, many researchers have focused on this issue and have tried to apply machine learning and deep learning methods in agriculture under the name of smart farm technologies both to increase agricultural production and to solve some challenges of agriculture. In this study, it is aimed to give detailed information about these up-to-date studies. 77 articles based on machine learning and deep learning algorithms in the agriculture field and published in IEEE Xplore, ScienceDirect, Web of Science and Scopus publication databases between 2016 and 2020 years were reviewed. The articles were classified under five categories as plant recognition, disease detection, weed and pest detection, soil mapping-drought index, and yield forecast. They were examined in detail in terms of machine learning/deep learning architectures, data sets, performance metrics (Accuracy, Precision, Recall, F-Score, R^2, MAPE, RMSE, MAE), and the obtained experimental results. Based on the examined articles, the most popular methods, used data sets/types, chosen performance criteria, and performance results among the existing studies are presented. It is seen that the number of AI-based applications related to agriculture is increasing compared to the past and the sustainability in productivity is so promising.

1. Introduction

The mind is formed by the combination of thinking, comprehension, understanding, decision-making, reasoning, and knowledge power [1]. Intelligence combines all these goals and making them suitable for the situation [2]. Artificial intelligence brings in all these abilities to the machine. Artificial intelligence is an effort to make the computer do what people do [3]. Today, artificial intelligence studies conducted in many fields are also carried out in the field of agriculture. Given the fact that the world population is increasing rapidly, agricultural products and nutrition are critical for the continuation of human life. People have made radical changes in agricultural products by the discovery of modern agriculture [4]. Besides, the supply and production of agricultural products have a great importance in the global economy [5]. The decrease in agricultural production due to the effect of global warming, drying of wetlands, unconscious irrigation and unconscious agriculture poses a great danger to world population. Because of these effects, the amount of nutrition is increasing in parallel with the rapid increase in the world. Looking at the developments, it seems that smart farming has become critical to overcome the challenges [6].

Machine learning (ML) has emerged with big data and high performance and is actively used in many areas of the industrial environment such as entertainment and commerce [7]. Machine learning has started to create opportunities in agricultural fields by using the learning

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abilities of measuring and understanding data. Deep learning (DL) is a branch of machine learning that tries to model abstractions with a series of algorithms by using a deep layer with multiple processing layers [8]. Deep learning, which is of great interest in the field of artificial intelligence, has come to the fore in natural language processing and image classification. In this study, previous studies on deep learning and machine learning in agriculture applications were examined. Articles published between 2016 and 2020 in the most well-known and used databases (IEEE Xplore, Science Direct, Web of Science, Scopus) were searched using the keywords “Machine Learning in Agriculture” and “Deep Learning in Agriculture”. 7 studies from 2016, 9 studies from 2017, 14 studies from 2018, 29 studies from 2019, and 18 studies from 2020 were examined. While 71% (55 articles) of the 77 articles were related to the United States, United Kingdom, China, India, Spain and Australia, 29% of them (22 articles) were related to other countries.

While ML and the most used ML methods were defined in the *second section*, DL and the most used DL methods were defined in the *third section*. Articles and applications related to ML and DL in agriculture were reviewed in the *fourth section.*

2. Machine Learning

ML refers to the process of creating a mathematical model on sample data sets called training data to make predictions and decisions [9]. ML, a sub-branch of artificial intelligence [90] and developed based on learning models, is a system that investigates the working principle of algorithms that can make predictions through data (Figure 1). The data to be used for prediction is trained and classified (Dataset) with a ML algorithm. The test (sample) data are appropriately classified according to the data being trained (Figure 2). Depending on their learning skills, ML algorithms are divided into three separate categories as Supervised, Unsupervised and Reinforcement Learning. Classification and Regression Models are examined in the *supervised learning* category. Clustering and Dimensionality Reduction are examined in the *unsupervised learning* category and Real-Time Decisions models are examined in the *reinforcement learning* category. Supervised learning makes predictions over the designed model by using input data. Unsupervised learning performs more complex processing tasks. Dimension reduction is a method that can be analyzed with both supervised and unsupervised learning methods. PCA (Principal Component Analysis), PLSR (Partial Least Squares Regression) and LDA (Linear Discriminant Analysis) are the most known and used dimensional reduction algorithms. ML techniques are generally used to analyze human behavior benefiting from available data, enable businesses to carry out production accordingly, and also to create business models and decision support systems. Especially, behaviors of individuals are analyzed through online shopping, social media, e-mail contents, etc. and characteristics of human behavior can be determined. Today, many cellphones, laptops and electronic devices use various ML-based applications for different purposes.

3. Deep Learning

Deep learning (DL), first pronounced by Igor Aizenberg in the early 2000s, became more popular in 2016 [10]. DL gives more depth and complexity to the model and improves the classic ML model through transforming data into various levels of abstraction by using artificial neural network (ANN) or similar ML algorithms [11].

DL is a much more advanced model of ANNs. While ANNs consist of three layers (input, output and hidden layers), networks with more than one hidden layer number are called deep learning. DL produces an output by self-learning the information passed through hidden layers as seen in Figure 3. It has algorithms such as Convolutional Neural Networks, Recurrent Neural Networks, Restricted Boltzmann Machine, and Deep Belief Network [12]. DL has the advantages of processing unstructured data at the maximum level, producing high quality results, and avoiding unnecessary costs. On the other hand, it has some disadvantages such as needing much larger amount of data and high cost for software and hardware. It is used in a wide range of areas including natural language processing, driverless vehicles, image processing, face recognition, and personalized shopping planning.

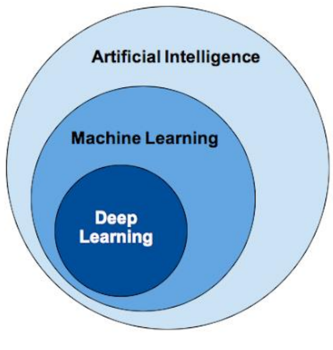

Figure 1. Relationship between DL and ML

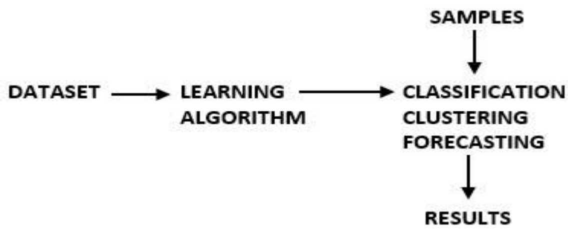

Figure 2. Machine Learning Architecture

4. Methodology

We carried out literature review of academic articles indexed on the Scopus, Web of Science, Science Direct and IEEE Xplore to asses the extent to which ML and DL features with in the agriculture. We have analyzed and classified articles in two fields which are ML and DL. These articles have been explored in details based on various features such as years of the studies, aim of the studies (plant recognition, disease detection, weed and pest detection, soil mapping-drought index and yield forecasting), properties of the datasets used in the studies, architectures, performance criteria examined in the studies and received results.

4.1. Data

As mentioned in methodology, the study containes articles from four well-known databases such as Scopus, Science

Direct, Web of Science and IEEE Xplore. The main reason for selection of these databases is that they are considered to include the highest quality and up-to-date publications. In order to list the up-to-date publications to readers, data used for this study were collected from January to June 2020 for the years from 2016 to 2020 with the keywords "*Machine Learning in Agriculture*", "*Deep Learning in Agriculture*". The study was conducted as a doctoral thesis. As the final dataset, 77 articles within the scope of studies similar to doctoral thesis have been reviewed. Of the total 77 articles reviewed, 10 were on plant recognition, 16 were on disease detection, 9 were on weed and pest detection, 26 were on yield forecasting and 16 were on soil mapping, drought index and other studies.

4.2. Studies on ML and DL

In this section studies related to ML and DL are classified according to their fields. Of the total 77 articles reviewed, 10 were on *Plan Recognition*, 16 were on *Disease Detection in Plants*, 9 were on *Weed and Pest Detection*, 26 were on *Yield Forecasting* categories, and 16 were on *Soil Mapping, Drought Index and Other Studies*.

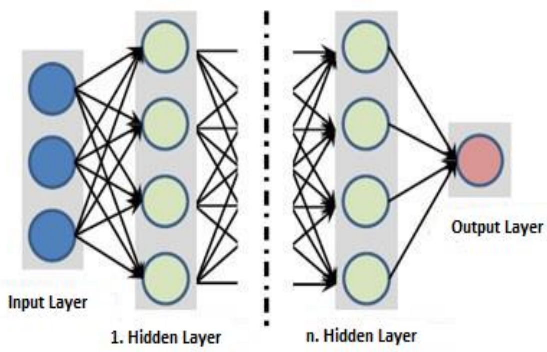

Figure 3. Deep Learning Architecture [8]

4.2.1. Plant Recognition

Identification of the plant species has been realized with ML and DL methods depending on classification algorithms in smart agriculture applications based on artificial intelligence (Table A.1 in Appendix). 126 citrus images obtained in different sizes and under various lighting conditions were trained with ML algorithms and a study was carried out to determine the green citrus fruit [13]. Plant species were classified using DL algorithms on many images obtained from 1200 Turkey TARBIL station [14]. Similarly, a various plant type was classified with DL algorithms by using the half-hour images obtained from the Turkey TARBIL system [15]. Coffee leaf rust was modeled with images obtained using a hand-made spectroradiometer [16]. Product type recognition was carried out with ML algorithms using 126 Rice, Corn and Soybean plant images obtained from 2017 Sentinel-II satellite [17]. Determination of wheat nitrogen and water status was carried out using data combined with annual rainfall data [18]. Using DL algorithm, 450 images of Lycopersicon were classified into three different level as mature, semi-mature, and immature [19]. In order to detect Convolvulus Sepium plant in sugar beet fields and to detect changes in the appearance of sugar beet plants, necessary detection process was performed on 2271 synthetic images of 452 areas [20]. A hybrid algorithm was developed to estimate size of rice kernels, and data sets containing long, medium and short grain rice images were used in three separate data sets for training model [21]. Flaws of the lemon fruit were detected by using ML and DL methods on 341 images (185 healthy shaped, 156 damaged shaped) of sour lemon with different shapes, and accordingly lemons were classified [22].

4.2.2. Disease Detection in Plants

One of the most important problems in agriculture and the production of agricultural products is plant diseases. To prevent this, pesticides are sprayed homogeneously on the crops, or weeds are cleaned with the help of manpower to prevent and control harmful organisms. However, while doing this, labor, financial issues and time costs are high. In order to prevent these diseases and reduce time and cost, studies have been carried out on smart farming systems with ML and DL-based algorithms (Table A.2 in Appendix). In literature; the hybrid model developed for multi-class classification problems was applied on the traits that trigger oilseed disease [23]. Multicolor fluorescent imaging was applied together with thermography in order to detect soft rot caused by Dickeya Dadantii (Negative Bacteria) in the pumpkin plant [24]. An improved moth flame approach was proposed to detect tomato diseases, and the proposed algorithm ensured the highest classification accuracy [25]. A technique for disease detection and classification was explained with the aid of ML mechanisms and image processing tools [26]. Symptomatic recognition of four diseases of cucumber (anthracnose, downy mildew, powdery mildew, leaf spots) was tried to be detected using DL algorithms [27]. Detection of diseased melon leaves was performed using ML-based algorithms on numerical data provided through various imaging techniques [28]. It was aimed to develop an automated proof of concept by using images of A. Psidii disease in lemon tree [29]. A new Exponential Spider Monkey Optimization, which was used to fix important features from high dimensional features created by SPAM, and supported by SVM was developed, and it was compared with other ML algorithms to classify plants as healthy and diseased images [30]. It was aimed to detect diseases in red vine leaves by using yellowing and severe symptoms of grape leaves on color images of Grapevine Yellow leaves [31]. A multi-layer DL algorithm was developed to identify anthracnose disease and symptoms in mango leaves [32]. A model using the ML algorithm was proposed to detect rice blast disease in the early stages of cultivation [33]. A method was developed to detect diseases through plant leaf images by using the TensorFlow object detection API [34]. An automatic identification method was developed for diseases, such as healthy, downy mildew, powdery mildew and rot, in various leaf sample images corresponding to different product types [35]. An onion area was regularly monitored through the established monitoring system and the symptoms of the disease were tried to be determined by creating four different models based on the images obtained [36]. Disease detection was performed with DL algorithms over a data set containing various disease images in order to detect disease types in tomato, potato, corn, and apple plants [37]. Cassava plant diseases have been tried to be determined by using the category of cassava leaf disease [38].

4.2.3. Weed and Past Detection

Weed and pest detection is one of the major problems in agriculture for crop production and has turned into a serious problem for many producers. Weed and pest detection is crucial for sustainable agriculture. For this purpose, in studies related to smart agriculture, detection studies have been carried out by using ML and DL methods (Table A.3 in Appendix). In literature; a hybrid algorithm consisting of Deep-CNN and SVM was used to identify and classify 22 different Lepidoptera (Butterfly) species on 1301 images [39]. Anastrepha fruit fly species were determined by using ML algorithms in order to avoid insect analysis time and economic losses related to agricultural pests [40]. For pest detection, a DL-based algorithm was proposed for the development of an agricultural pest identification system based on computer vision technology [41]. A DL-based approach aimed at weed specific herbicide application was proposed to detect weeds on soybean images and classify weeds [42]. The characteristics of the pest images were determined from a large number of unlabeled image structures by using unsupervised learning methods [43]. Spanish phytosanitary products were classified using four separate ML algorithm methods in order to classify pesticide regulations correctly [44]. An ML-based algorithm was developed for weed and crop separation, and their accuracies were compared with NDVI values [45]. A large-scale study was conducted at 336 French sites to determine crop damage caused by the presence of wireworm and raiding species [46]. DL-based approaches were used for foreign object analysis through images obtained with UAV at four different times in two different rice fields [47].

4.2.4. Soil Mapping, Drought Index and Determining Agricultural Vehicles

It is important to determine suitable soil types for agriculture and to prepare drought index. In this context, studies conducted for soil mapping and determination of drought index were analyzed. The reviewed articles related to weed and pest detection are presented Table A.4 (in Appendix); A variance-based solution was proposed to identify the central pivot irrigation system and position the center of each central pivot system at a more effective point [48]. A geoparser-based soil mapping was proposed, and by applying ML methods, establishing the relationship between the phosphorus in the soil and the environment was tried [49]. SDAP model was proposed to predict drought areas without meteorological data and assuming no rainfall. This study was carried out for short-term drought prediction [50]. The temporal behavior of the soil ground was estimated using two separate ML algorithms, and Meteorological data were used as input [51]. A DL-based model named AMTNet was designed for the identification and classification of agricultural machinery [52]. A medium resolution imaging spectroradiometer was used to measure the surface temperature of the land up to 90 meters and to make a comparison between ML-based algorithms by scaling the image [53]. Neural networks offer real-time computational flow. The load on the neural network was restrained and the pretreatment by removing the plants from the background was briefly discussed [54]. A hybrid heuristic method was developed to estimate the irrigation time and find the most suitable decision tree to model the farmers' behavior [55]. To monitor agricultural drought data in Southeast Australia, an attempt was made to estimate drought over wheat yield by using SPEI data sensed remotely by the Tropical Rainfall Measuring Mission and MODIS satellite [56]. ML algorithms were used to define the relationships between soil properties and multiple common variables that can be detected in the landscape, and the most appropriate ML algorithm was selected for digital soil mapping (DSM) [57]. New approaches were proposed to map the agricultural drought hazard by using machine learning methods [58]. The potential of the DL approach to automatically draw agricultural plot boundaries from orthophoto images in large areas with a heterogeneous landscape was explored [59]. The crop drought mapping system was implemented by evaluating crop stress with RGB images obtained from UAV vehicles [60]. DL-based models were examined to calculate the crop water stress index (CWSI) which is one of the parameters obtained from the vegetation temperature and measured in open irrigation [61]. A new drought index (IDI) that defines the multivariate relationship between agricultural drought conditions was proposed [62]. A hybrid model was developed by combining the global climate model and ML-based model to forecast 90-day weather on field scale [63].

4.2.5. Yield Forecasting

Depending on the increasing world population, increasing agricultural productivity has come to a very important point. The reviewed articles related to yield forecasting are presented in Table A.5 (in Appendix). It was tried to predict wheat yield through images obtained from different soil and crop sensors by using an unsupervised learning algorithm [64]. An ML-based model was applied to estimate the NDVI values of large pastures in the USA. The prediction model consisted of data on vegetation index and meteorological factors [65]. A hybrid approach was proposed to perform yield classification of sugarcane based on various soil and climate parameters [66]. A classification model was developed to predict the production in an orchard and determine the effects of ML-based models and factors on production [67]. Two separate artificial intelligence models were developed to predict ET0 (Evapotranspiration) by using only temperature data in Sichuan region of China [68]. ML-based models were used to define the importance of remotely sensed image variables in the spatial prediction of soil and maize yield [69]. A collection of 76 regressors was proposed for the estimation of soil organic carbon productivity indices of four important soil nutrients [70]. An ML-based prediction model was developed to determine and map cotton lint yield in a 73-hectare field in Tennessee, USA [71]. Three separate DL-based simulation models were carried out to predict the rapeseed (canola) plant before harvest and to determine the most important independent variables affecting the yield of rapeseed [72]. The possibility of using ML algorithms was examined on the satellite images obtained to evaluate the spatial variation of corn grain yield in cropland scale, and the measured yield was analyzed [73]. An attempts was made to estimate wheat yield in Australia by looking at time series-based climate records and satellite images [74]. A DL-based model was developed to estimate the number of seeds from soybean images [75]. Participants were asked to predict their yield performance using data from 2017, and a model based on DL algorithms was developed at the Syngenta Crop Competition in 2018 [76]. Yield estimation study was carried out using data on wheat, barley and canola crops as a case study on a large farm in Western Australia [77]. Phenotype characteristics of trees belonging to 25 different rootstock varieties on orange yield were determined using high-type phenotyping system on images obtained by UAV [78]. A software called AirSurf, which was an open-source hybrid system, was developed to automatically measure yield related phenotypes on ultra-large aerial images for lettuce [79]. A ML-based model was developed to estimate the amount of carbamazepine (CBA) and diclofenac (DCF) in tissues of lettuce plants irrigated with water recovered from water treatment plants [80]. ML methods were used to estimate interpolation accuracy by using greenhouse environment data, and the results were compared with each other [81]. An ML approach was used to increase crop yields based on crop planting dates and to estimate the annual crop planting date [82]. ML approaches were used to estimate ET0 (Evapotranspiration) by using data from the Verde Grande River basin [83]. A new criterion was introduced to determine daily ET0, improve classification efficiency, educate, and validate for the regions of Hoshiarpur and Patiala, Punjab state of India [84]. A segmentation method based on DL model was implemented to automatically perform the segmentation task [85]. A case study on maize production was conducted to predict global warming and eutrophication effects, and ML algorithms were compared to determine the most efficient and accurate model [86]. An ML-based prediction model was developed to measure global warming and eutrophication effects on the life cycle of corn production [87]. ML-based models were used to evaluate moisture content and fruit quality for apple and mango plants [88]. An architectural model was developed to assess soil fertility and productivity and to make farming more efficient and productive with minimal impact on the environment [89].

5. Results and Discussions

It was determined that while 50% of the reviewed studies on *plant recognition* involved DL models, other studies involved the use of ML methods and the comparison of the results of the performance metrics of these methods. While the most preferred DL models were CNN-based models, SVM and ANN algorithms were used more in ML methods. It was seen that 10% of the studies on plant recognition were carried out by implementing a hybrid model using ML algorithms. The hybrid model was created with the combination of five different ML algorithms (SVM, ANN, RF, KRR, and KNN). It was observed that models were mainly evaluated by looking at accuracy, precision, recall, and F1-Score metric values in the studies performed using both methods (ML and DL). The most studied agricultural product was rice in plant recognition.

While 37% of the examined studies on *disease detection* in plants were carried out with DL models, 50% of them were realized with ML algorithms and 13% were carried out by using hybrid models. While studies on DL were carried out with CNN and CNN-based models, ML studies were carried out using SVM and ANN algorithms. While one of the two studies created using hybrid models was performed with DL, CNN-based models were used as a model. Another hybrid model was realized with ML methods and this model was a combination of logistic regression and naive bayes algorithms. The most studied agricultural product was tomato.

While 55% of the studies on *weed and pest detection in plants* were carried out on pest detection, 45% was carried out on weed detection. 50% of the studies carried out with *pest detection* was realized with DL methods, the other 50% was realized with ML methods. CNN and CNN based AlexNet, ResNet-50, and ResNet-101 models were used as ML methods. MLP, SVM, LR and RF algorithms were used as ML algorithms. While CNN and CNN-based FCNN and AlexNet were preferred as DL methods in studies carried out with *weed detection*, SVM, LR and RF algorithms were preferred as ML algorithms. The results obtained by all methods were compared with each other's performance criteria and the best model was selected.

While 11 of 16 studies on *soil mapping, drought index and determination of agricultural vehicles* were carried out for the detection of agricultural drought, 4 of them were for soil mapping, and 1 of them was for identification of agricultural vehicles. Of the 11 studies conducted for the *detection of agricultural drought*, 4 were carried out with DL methods, 5 were carried out with ML methods, and 2 were implemented with hybrid models developed with ML methods. CNN and CNN based LeNet, AlexNet, VGGNet, SegNet models were used as DL models. ANN, RF, SVM, MLP algorithms were used as ML models. While one of the implemented hybrid models consisted of the combination of decision tree and genetic algorithm, the other hybrid model was created by combining ELM and GloSea5GC2 climate model. *Of 4 studies conducted for soil mapping*, 1 was carried out with DL methods, the others were carried out with ML methods. CNN algorithms were used as DL model, ANN, SVM and RF algorithms were used as ML models. Only one study was carried out for *determining agricultural vehicles*, and Google Inception v3 and ResNet-50 models were used for that study. Accuracy, precision and error averages of models and algorithms were examined throughout the studies and algorithms, and models were compared based on these values.

73% of the applications realized for yield forecasting were carried out with ML methods. The most used ML algorithms were ANN, SVM, Decision Tree, LR, RF, and MLP. CNN and CNN-based model, which was SegNet, were used as a DL method. MAE, R^2, RMSE, and correlation coefficient values were checked to compare the results of the algorithms and models in general. The most studied agricultural products in terms of yield were corn, wheat, lettuce crop amount, and Evapotranspiration value.

It is seen that the use of image data obtained from different sources is widespread thanks to the advances in image processing methods in ML and DL. Especially CNN based architectures are so popular.

The articles reviewed in the presented paper has been classified according to the aims of the studies and shown in Table 1. And another classification according to the years of studies in publication databases and shown in Table 2 below. When the two tables are examined, it is seen that most of the presented studies aims on yield forecasting. Most of the papers about agriculture has been listed in Scopus. As the end of the article collection process was June of 2020, number of listed studies in 2020 is smaller than 2019. But it is generally seen that the number of studies are increasing in recent years. It is thought that scientific studies in agriculture have increased due to the increasing importance of agriculture.

Table 1. Classification of Studies by Years and Aims

Years	**Plant Recognition**	**Disease Detection**	**Weed and Pest Detection**	**Soil Mapping**	**Yield Forecast**	**Total**
2016	2	2	0	0	3	7
2017	1	2	4	0	2	9
2018	1	4	4	2	3	14
2019	3	5	0	8	13	29
2020	3	3	1	6	5	18
Total	10	16	9	16	26	77

Table 2. Reviewed Articles in Academic Databases by Years (WOS: Web of Science, SD: Science Direct, IEEE: IEEE Xplore, SCO: Scopus)

Years	**WOS**	**SD**	**IEEE**	**SCO**	**Total**
2016	0	1	0	6	7
2017	0	0	0	9	9
2018	0	4	0	10	14
2019	4	4	5	16	29
2020	9	6	1	2	18
Total	13	15	6	43	77

6. Conclusion

ML and DL are two of the popular subsets of today's AI technology and used in various areas such as health, manufacturing, network, etc. As importance of agriculture is increasing in parallel with the population of the world, the scientists have focused on increasing the productivity in agriculture. Many studies about this topic have been conducted in the literature. For the purpose of providing up-to-date information to researchers, ML and DL-based articles about agriculture published in well-known publication databases, such as IEEE Xplore, ScienceDirect, Web of Science and Scopus, between 2016 and 2020 years were reviewed and presented in this study.

The articles were classified according to their main purposes, such as plant recognition, disease detection, weed and pest detection, soil mapping-drought index-determining agricultural vehicles, and yield forecasting. The review of the studies showed that while the most preferred ML models were SVM, ANN, and RF, the most preferred DL models were CNN-based models which were AlexNet, LeNet, and ResNet-50. However, hybrid models of DL and ML were also used. Generally used performance criteria for both ML and DL models were accuracy, precision, F1-score, and recall. The most popular plant and agricultural products used in experiments were wheat, corn, rice, tomato, sugarcane, and soybean. Although most of the studies used images taken from drones or satellites, some studies also used meteorological data.

It is seen that the number of AI based-applications in agriculture is increasing compared to the past and this is very promising in terms of the sustainability in productivity.

Declaration

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The authors also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

This study was prepared within the scope of a doctoral thesis. F. Bal is the PhD student and the F. Kayaalp is the supervisor. Conception and design of the study has been implemented by F. Kayaalp. After the acquisition of data, analysis and drafting of the manuscript has been carried out by F. Bal. Revising the manuscript critically in terms of important intellectual content has been performed by F. Kayaalp.

Nomenclature

AlexNet	: An another model of CNN (Designed by Alex Krizhevsky)
AMTNet	: A version of Inception_v3 Network
ANFIS	: Adaptive Network Based Fuzzy Inference System
ANN	: Artificial Neural Networks
API	: Application Programming Interface
BP Network	: Back Propagation Network
BRT	: Boosted Regression Tree
CART	: Classification and Regression Trees
CNN	: Convolutional Neural Networks
CWSI	: Crop Water Stress Index
D-CNN	: Deep CNN
DL	: Deep Learning
DSM	: Digital Soil Mapping
D-Tree	: Decision Tree
ELM	: Extreme Learning Machine
ET0	: Evapotranspiration
FCNN	: Fully Convolutional Neural Networks
KNN	: K-Nearest Neighbors
KRR	: Kernel Ridge Regression
LDA	: Latent Dirichlet Algorithms
LeNet	: An another model of CNN (Designed by Yann LeCun)
LR	: Logistic Regression
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percentage Error
MARS	: Multivariate Adaptive Regression Spline
ML	: Machine Learning
MLP	: Multi-Layer Perceptron
MODIS	: Moderate Resolution Imaging Spectroradiometer
NB	: Naive Bayes
NDVI	: Normalized Difference Vegetation Index
PLSR	: Partial Least Squared Regression
PSO	: Partial Swarm Optimization
RBF	: Radial Basis Function
RF	: Random Forest
RGB	: Red-Green-Blue colors
RMSE	: Root Mean Squared Error
SDAP	: Severe Drought Area Prediction
SegNet	: Semantic Segmentation
SPAM	: Subtractive Pixel Adjacency Model
SPEI	: Standardized Precipitation-Evapotranspiration Index
SVM	: Support Vector Machine
TARBIL	: Tarımsal İzleme ve Bilgi Sistemi (Agricultural Monitoring and Information System)
UAV	: Unmanned Aerial Vehicle
USA	: United States of America
VGGNet	: Visual Geometry Group (Designed by VGG from Oxford University)

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Appendix

Table A.1. Studies on plant recognition

Article	Year	Plant	Dataset	Model/ Algorithm	Result
[13]	2016	Citrus	RGB images of 126 citrus fruits	SVM	Accuracy SVM: 83%
[14]	2016	Various Plant Images	Images obtained from 1200 Turkey TARBIL stations	CNN, SVM-Kernel, SVM-Polynomial Kernel	Accuracy CNN: 100%, SVM: 91.2%, D-Tree: 81.5%, ANN: 93%, kNN: 83.6%
[15]	2017	Various Plant Images	The half-hour AlexNet images obtained from Turkey TARBIL system		**For Wheat**; CNN Precision: 82.62%, Recall: 83.64%, F1-Score 83.68%, Accuracy: 83.64%, MEF-BA precision: 75.51%, Recall: 74.53%, F1-Score: 74.57%, Accuracy: 74.53%; **For Barley**, CNN Precision: 79.32%, Recall 77.34% F1-Score: 78.43%, Accuracy: 77.15% MEF-BA Precision: 72.21%, Recall 71.68%, F1-Score: 72.21%, Accuracy: 71.43%
[16]	2018	Various Plant Images	Images obtained using a spectrodiometer	RBF-PLS, CLR	For RBF-PLS; R^2: 0.27, RMSE: 18.7 For CLR; R^2: 0.92, RMSE: 6.1
[17]	2019	Rice, Corn, Soybean	Images of Rice, Corn, Soybeans obtained from Sentinel-II satellite in 2017	RF, SVM	Accuracy RF: 88.6%, SVM: 98%
[18]	2019	Wheat	Average annual rainfall data for the years 2012, 2013, 2014 and combined data	PLSR	Accuracy RF: 88.6%, SVM: 98%
[19]	2019	Tomato	450 images obtained on ImageNet	CAE, CNN, SoftMax	F1-Score CNN+SoftMax: 99.63% CAE+CNN+SoftMax: 100% CNN+SVM: 100% CAE+CNN+SVM 100%
[20]	2020	Sugarcane	2271 Synthetic images in 452 different area	CNN Algoritmaları: Yolo v3, Yolo v3-Tiny	MAPE Values; Yolo v3: 0.832 Yolo v3-Tiny: 0.810
[21]	2020	Rice	CL153 (Long grain dataset) Jupiter (Medium grain data) Calhikari 202 (Short grain dataset)	SEM Hibrit Modeli: RF, ANN, SVM, kRR, kNN	MEAN ERROR For CL153 dataset: 4.1% Jupiter dataset: 2.9% Calhikari for dataset: 4.3% has error rate.
[22]	2020	Sour Lemon	341 Sour lemon images (185 health shapes, 156 damages shapes)	CNN, SVM, D-Tree, ANN, kNN	Accuracy CNN: 100%, SVM: 91.2% D-Tree: 81.5%, ANN: 93% kNN: 83.6%

Table A.2. Studies on detection of plant diseases

Article	Year	Plant	Dataset	Model/ Algorithm	Result
[23]	2016	Various Plant Images	A total of 13360 images from different sources	Hybrid Model (Logistic Regression and Naive Bayes)	Accuracy Hybrid Model: 94.73%
[24]	2016	Pumpkin	Many images of the pumpkin plant	Logistic Regression, ANN	LR, high dose-infiltrated leaves; YSA, low dose-infiltrated leaves. High accuracy predicted by rates.
[25]	2017	Tomato	Adult, Zoo, Lung, taken from the UCI ML pool Soybean-small, Monk's datasets	KNN, SVM	MFORS-kNN Accuracy:84%, Precision:84.2%, Recall: 83%; MFORS-SVM Accuracy: 84%, Precision 86%, Recall 87%
[26]	2017	Various Plant Images	250 images of 5 different diseases	SVM	Accuracy SVM: 94.2%
[27]	2018	Cucumber	14208 symptom images	D-CNN, RF; SVM, AlexNet	Accuracy D-CNN: 92.2%, AlexNet: 82.6%, SVM: 81.9%, RF 84.8%
[28]	2018	Melon	358 images between 3-7 DPI	LR, ANN, SVM	Accuracy LRA: 96.5%, SVM: 98.3%, ANN 99.1%
[29]	2018	Lemon	135 images of untreated lemon trees	RF	Accuracy RF: 95%

Article	Year	Plant	Dataset	Model/ Algorithm	Result
[30]	2018	Various Plant Images	Image dataset from PlantVillage (500 healthy, 500 unhealthy)	SVM, LDA, kNN, ZeroR	Accuracy ESMO-SVM: 92.12%, ESMO-LDA: 80.79%, ESMO-kNN: 84.76%, ESMO-ZeroR: 49.32%
[31]	2019	Grape	Image dataset from PlantVillage in Tuscon region between July and October	AlexNet, GoogleNet, Google Inception v3, ResNet-50, RestNet-101 SqueezeNet	Accuracy AlexNet: 97.63%, GoogleNet: 96.36%, Google Inception v3: 98.43%, ResNet-50: 99.18%, ResNet-101: 99.33%, SqueezeNet: 93.77%
[32]	2019	Mango	1070 real-time environment images, 1130 images from the PlantVillage dataset. 2200 images in total	PSO, SVM, RBF, MCNN	Accuracy PSO: 88.39%, SVM: 92.75%, RBFNN: 94.20%, MCNN: 97.13%
[33]	2019	Rice	350 images for rice	kNN, ANN	Accuracy kNN for explosion image 85%, for normal image 86%; ANN for explosion image 99%, for normal image 100%
[34]	2019	Various Plant Images	236 healthy plants images; COCO dataset	R-CNN	Accuracy R-CNN: 67.34%
[35]	2019	Various Plant Images	Images obtained from smart phone and tablet	One Class SVM	Accuracy SVM: 95%
[36]	2020	Onion	Obtained real time images for onion	CNN	MAP; For A model: 75.0% For B model; 74.1% For C model: 81.8% For D model: 87.2%
[37]	2020	Tomato, Potato, Corn, Apple	Images of plant diseases 36,000 images	Wide Residual Networks, Google Inception v4	Accuracy WRN: 91.03% Google Inc. v4:57.26%
[38]	2020	Cassava	10,000 images of 5 fine-grained Cassava roots	CNN	Accuracy CNN: 94%

Table A.3. Studies on weed and pest detection

Article	Year	Plant	Dataset	Model/ Algorithm	Result
[39]	2017	Lepidoptera (Butterfly)	1301 images of 22 Lepidoptera species	CNN	LLC and CART method 95% His own methods 100%
[40]	2017	Anastrepha (Fruit Fly Pest)	301 images divided into different categories	MLP, NB, D-Tree, NB-Tree, kNN, Simple LR, SVM	Accuracy MLP: 88.9%, NB: 58.9%, D-Tree: 70.6%, NB-Tree: 71.6%, kNN: 79.5%, Simple-LR: 79.2%, SVM 87.7%
[41]	2017	Various Pest Images	Pest Images obtained from mixed agricultural land	SVM, BP-NN, AlexNet, ResNet-50, ResNet-101	Accuracy ResNet-101: 98.67%, ResNet-50: 94.67%, AlexNet: 86.67%, SVM: 44.00%, BP-NN: 42.67%
[42]	2017	Weed	Images acquired between 08:00 and 10:00 in the morning between December 2015 and March 2016	CaffeNet, SVM, AdaBoost, RF	Precision CaffeNet: 98%, SVM: 95%, AdaBoost: 96%, RF: 95%
[43]	2018	Various Pest Images	4500 pest images for D0 area 1440 butterfly images for D1 area 60 images of 24 pest kind pest images for D2 area 225 insect images for D3 area	Unsupervised Dictionary Learning	Accuracy For D0: 83.5% For D1: 97.2% For D2: 90.0% For D3: 91.5%
[44]	2018	Weed	Consisting of 25 420 words and 1135 rules a data set	LR, SVM, RF	Accuracy LR: 84.46%, RF: 84.04%, SVM 72.12%
[45]	2018	Weed, Beet, Corn	146 images of beet and corn plants	Gauss-SVM	Accuracy Gauss-SVM: 97%, NDVI: 70%
[46]	2018	Wireworm	14% of the land area and Data from Murray-Darling Basin covering 67% of agricultural land	ELM, RF	For ELM R values: 0.641, RMSE: 0.641, MAE: 0.055; For RF R values: 0.829, RMSE 0.056, MAE: 0.044
[47]	2020	Weed	364 pest images in F1 area, 240 pest images in F2 area	BP Network, SVM, RF, FCNN	In OBIA analysis MIU values 66.6% and 2343.5 inference speed, and FCN 80.2% and 326.8 inference speed

Table A.4. Studies on soil mapping, drought index and determining agricultural vehicles

Article	Year	Plant	Dataset	Model/ Algorithm	Result
[48]	2018	Drought	Images obtained from Landsat 5-TM satellite between 1986-2000	LeNet, AlexNet, VGGNet	Accuracy LeNet: 100%, AlexNet 99.92%, VGGNet 99.93%
[49]	2018	Soil Mapping	69562 images of multispectral area	ANN, RF	For ANN; ME 2.85, RMSE 23.64 For RF; ME 3.19, RMSE 22.53
[50]	2019	Drought	Images obtained from the 97-day Landsat-8 satellite between March 2017 and June 2017	RF	First model; RMSE: 0.052, MAE: 0.039, R^2: 0.91. Second model; RMSE 0.382, MAE: 0.375, R^2: 0.58
[51]	2019	Drought	Meteorological data obtained from SWI	ANN, ANFIS	For ANN; NSE: 0.371, RMSE: 2.654 For ANFIS: NSE 0.460, RMSE 2.459
[52]	2019	Agricultural Machinery Classification	7 models of agricultural machines are divided into 6 types according to shooting angle; 125,000 images in total	Inception v3, RestNet-50, AMTNet	For Top_1 Dataset: 97.83%, For Top_5 Dataset: 100%
[53]	2019	Soil Mapping	DEM data obtained from NASA's Shuttle Radar Topography	ANN, SVM, RF	For RMSE; ANN: 2.62, SVM: 2.82, RF 2.22
[54]	2019	Drought	80,000 images of 12,517 plant	CNN	For Carrot; Precision: 99.68%, Recall: 99.56, F-Score: 0.9962. For Herb; Precision: 99.57%, Recall: 99.68%, F-Score: 0.9962
[55]	2019	Drought	Values for 228,855 irrigation events were used in the 365-day evaluation of the 2,891-hectare Sector 2 in Spain's 21,141 hectare Canal del Zujar (CZD) region.	Hibrit (D-Tree ve Genetik Algoritma)	Accurate irrigation events between 68%-100%, Inaccurate irrigation events between 93%-100%
[56]	2019	Drought	SPI (Standardized Precipitation Evapotranspiration Index), TRMM (Tropical Rainfall Measuring Mission) and MODIS data between 2001-2017.	Bias-corrected random forest, SVM, MLP Neural Network	Looking at the RMSE; Bias-corrected is more effective results from Random Forest
[57]	2020	Soil Mapping	Dataset A includes 200 sample data. Dataset B is a subset of A and includes 50 sample data. Dataset C includes 25 data of dataset B with largest residuals. Dataset D includes 25 data of dataset B with least residuals.	MLR, kNN, SVM, SVR, Cubist, RF, ANN	Calculation time is not important ANN works best. If the data set is less than 100 Cubist, RF, SVM, kNN good result gives.
[58]	2020	Drought	Hydraulic environmental datasets between 1994-2013	CART, MARS, BRT, RF	Looking at the ROC analysis RF is the best result the other models to 97.7%
[59]	2019	Soil Mapping	LPIS (Land-Parcel Identification System) data	CNN	To forecsast field areas 89%, To field border 69%
[60]	2020	Drought	Average temperature, precipitation sunny day rate and RGB field images from UAV, Chine Meteorological Administration in Dixing County	SVM	The pixel classification provided only 82.8% accuracy, with a low F1 score of 71.7%. Using spectral densities, it provided an accuracy of 89.9% with an F1 score of 87.7%.
[61]	2020	Drought	A total of 372 images taken in winter from lemon, orange, almond, olive, malt, fig, strawberry, cherry and walnut trees in Murcia, Spain (251 for SVM, 121 for deep learning)	SVM, SegNet	F1-Score; SVM: 83.11%, SegNet: 86.27%
[62]	2020	Drought	China Meteorological Information Center Meteorological data, agrometeorological data, remote sensing data and biophysical data between 2003-2014.	BP Neural Network	Recommended IDI system, SPI-3 and results close to SPEI-3 data produced.
[63]	2020	Drought	It was used by comparing Korea Meteorological Administration (KMA) forecast data and Met Office Global Seasonal Forecast Model v5 data.	Hybrid Model (Combined Extreme Learning Machine and GloSea5GC2 climate model)	Looking at the RMSE; Hybrid Model results between 1.02 and 3.35, and Climate Model results between 1.61 and 3.37

Table A.5. Studies on yield forecasting

Article	Year	Plant	Dataset	Model/ Algorithm	Result
[64]	2016	Wheat	Online satellite image	Counter-program ANN, XY-Fused Networks, Supervised Kohen Networks	CP-ANN: %78.3, XY-Fs – 80%, SKN 81.65%
[65]	2016	Three Different Vegetations	3 different vegetation index (AVHRR, MODIS, SPOT-4) for 32 years from NASA measures NDVI	ANN	Develop a model for daily in 16, 32, 48, 64 days and examine RMSE and MAPE values to each model
[66]	2016	Sugarcane	Nitrogen, Phosphorus, Potassium, Sulfur and total 20 data in Sugarcane field	Hybrid Model (DDNHL-GA), FCM-GA, GCM-DDHNL, NB, RBF Network, MLP, j48, Random Tree, LMT	Accuracy DDNHL-GA: 94.7%, FCM-GA: 93.4%, FCM-DDNHL: 92.1%, NB: 89.4%, RBF: 85.5%, MLP: 81.57%, J48: 73.68%, Random Tree: 71.05%, LMT: 86.84%
[67]	2017	Lemon, Mandarin, Orange	94 lemon images, 364 mandarin images, 509 orange images	M5 Prime	R (Correlation coefficient) Lemon 0.813, Mandarin 0.744, Orange 0.828 RMSE Lemon 0.072, Mandarin 0.165, Orange 0.297 MAE Lemon 0.107, Mandarin 0.081, Orange 0.102
[68]	2017	Evapotranspirati on	Meteorological data between 1961-2014 years in Sichuan, China	ELM, GRNN	1. Model ELM RMSE 0.198, MAE 0.267; GRNN RMSE 0.220, MAE 0.314 2. Model ELM RMSE 0.209, MAE 0.301; GRNN RMSE 0.194, MAE 0.263
[69]	2018	Corn	SOM, CEC, Mg, K and PH values for 200 soil at 2013, October 1 in Molly Caren Farm, Ohio	Linear Regression RF, Neural Network, Radial SVM, Linear SVM, Gradient Boosting Model, CU	Cross-Validation R^2; Linear 0,34, RF 0.53, SVM-R 0.45, SVM-L 0.33, GBM 0,41, NN 0,37, CU 0,52 RMSE Linear 1.15, RF 0,97, SVM-R 1,16, SVM- L 1,05, GBM 1,08, NN 1.12, CU 0,98
[70]	2018	Soil Fertility	372 data in Maharasthra, India	Neural Network, Deep Learning, SVM, RF, Boosting, Bagging, Bayesian Models, Extremely Randomized Regression Trees (extraTrees)	The best result is extraTrees for RMSE values between 0,57 and 0,70
[71]	2018	Cotton	400 images from 100 different cotton field and NCDC climate data between 2013-2014	ANN	ANN correlation R= 0,68 and MAE: %11
[72]	2019	Canola	Canola plant data between 2008-2015 and three separate datasets with 21 to 27 variables (QQWR15_4, QQWR31_5, QQWR30_6)	MLP	QQWR15_4 model MAE 0.2870, MAPE6.88, QQWR31_5 model MAE 0.4353, MAPE 9.87, QQWR30_6 model MAE 0.4118, MAPE 7.69
[73]	2019	Corn	721 images in 2016, 1552 images in 2017, 1566 images in 2018 obtained from Sentinel-II satellite	MR, RF, SVM, GNDVI	The highest R^2 GNDVI 0.48, The best results of R^2 for ML are RF which is 0,6. The best time to have a high corn yield is between 105 and 135 days after October
[74]	2019	Wheat	Satellite images and climate data of NDVI between 2009 and 2015 at an altitude of 250 meters, daily precipitation and weather data from SILO and images provided by farmers	RF, CUB, XB, SVM Linear, SVM Radial Basis, MLP, MARS, GP, kNN	Looking at the RMSE; The best result of RMSE is SVM Radial Basis Function (0.545.
[75]	2019	Soybean	500 Soybean images 32126 images containing seeds	CNN (3x3) CNN (5x5)	MSE; CNN (3x3): 23.49, CNN (5x5): 20.79, TCNN: 13.21
[76]	2019	Corn	2267 genotype of corn hybrid between 2008-2016 in 2247 location	DNN, Lasso, Shallow Neural Networks, Regression Tree	DNN RMSE 10.55, r 88.3; Lasso RMSE 20.28, r 36.68; SNN RMSE 12.96, r 80.21 RT RMSE 14.31, r 76.7
[77]	2019	Wheat, Barley, Canola	Precipitation and MODIS national-global dataset	RF	Correlation 0.89

Article	Year	Plant	Dataset	Model/ Algorithm	Result
[78]	2019	Orange	4931 tree images belonging to 25 rootstock varieties	CNN	Accuracy CNN: 99.9%
[79]	2019	Lettuce	Over 10000 training datasets with 20x20 pixels	Hybrid Model (AlexNet and CNN)	Accuracy 98%
[80]	2019	Lettuce	In a greenhouse with controlled temperature and humidity data followed for two weeks to determine CBZ and DCF intake by growing three types of lettuce	Hybrid Model (ELM and FFNN)	Accuracy for Hybrid Model 95%
[81]	2019	Mango	Mango greenhouse data from October 2016 and May 2018	MLP, RF, Spline, MVR, Linear	R^2 values In short term Linear %95, Long-term MLP %96
[82]	2019	Crop Forecast	Cropland Data Layer (CDL) data	Multi-layer ANN	Accuracy: %88 R^2: 0.9
[83]	2019	Evapotranspirati on	INMET data between 1996 and 2016 in Verde Grande River	HS, ANN, MLR, ELM	R (correlation coefficient) HS 0.661, MLR 0.731, ELM 0.724, ANN 0.718 RRMSE HR 0.171 MLR 0.091, ELM 0.151, ANN 0.165
[84]	2019	Evapotranspirati on	Meteorological data between 1978-1999 and 2007-2016 in Hoshiarpur, and between 1970-1999 and 2007-2016 in Patiala	ELM, GBM, GLM, DL-MLP	Nash-sutcliffe efficiency (NSE) 0.95-0.98, R^2 0.95-0.99, ACC 85-95, MSE 0.0369- 0.1215, RMSE 0.1921- 0.2691
[85]	2020	Various many plant images	365 images contain Simple-RGB and Foreground-RGB	SegNet	For Simple-RGB; Mean Accuracy 0.89, IoU 0.52, Boundary-F1 0.81 For Foreground-RGB; Mean Accuracy 0.94, IoU 0.58, Boundary F1 0.92
[86]	2020	Corn	For monthly weather forecast data; 4000 data to Scenario A and 6000 data to Scenario B	Linear Regression, SVM, MLP, GBP, Regression Tree, EGB	To Scenario A, GW Effects; Cross-validation correlation (CV CORR) values (LR-0.45, SVR-0.68, ANN-0.64, GBRT-0.80, XGBoost-0.78) To Scenario A, EU Effects; CV CORR values (LR-0.65, SVR-0.80, ANN-0.74, GBRT-0.87, XGBoost-0.86). To Scenario B, GW Effects; CV CORR values (LR-0.35, SVR-0.63, ANN-0.64, GBRT-0.78, XGBoost-0.76) Scenario B, EU Effects; CV CORR values (LR-0.63, SVR-0.74, ANN-0.74, GBRT-0.84, XGBoost-0.83)
[87]	2020	Corn	NASS fertilizer data, SSURGO data for soil type, NCDC monthly average temperature and precipitation data	The BRT model has been developed according to the life cycle of maize production for a period of 9 years.	Correlation coefficient between 0.87- 0,99, R^2 between 0.78- 0,82
[88]	2020	Apple and Mango	Terahertz data and Swisstol2 data (0,75 and 1.1 Thz frequency)	SVM, kNN, D-Tree	Accuracy For Apple SVM: 97.0%, kNN: 86.4%, D-Tree: 93.2; For Mango SVM: 93.4%, kNN: 86.4%, D-Tree: 92.5%
[89]	2020	Barley	Climatic events between 2001-2015 and data on 450 soils	PLSR (Partial Least Square Regression)	For Wheat RMSEC 0.20, R^2: 0.54 For organic matter; R^2: 0.9345, RMSECV 0.54%