"The Role of Artificial Intelligence in Modern Farming: A Review of Machine Learning and Deep Learning Techniques"

Mr. Sangamesh S K
Assistant Professor
Department of Computer Science and Engineering
Rural Engineering College, Hulkoti

Miss. Nandini Nandan
Student
Department of Computer Science And Engineering
Rural Engineering College, Hulkoti

Mrs. Pavitra M Gadhar
Assistant professor
Department of Computer Science and Engineering
K.L.E. Institute of Technology,Hubballi

ABSTRACT:

This review explores the utilization of machine learning (ML) and deep learning (DL) models in agriculture. It covers their applications in yield prediction, pest and disease detection, crop classification, and resource optimization. ML algorithms like SVM, RF, and neural networks aid in yield prediction, optimizing resource use. DL algorithms such as CNN and RNN excel in pest and disease detection, reducing crop losses. ML/DL also contribute to crop classification, weed management, and precision agriculture practices. Challenges include data quality, model interpretability, and scalability. Collaborative efforts and ongoing research are crucial for addressing these challenges and advancing ML/DL solutions in agriculture. Overall, ML and DL models revolutionize farming, offering data-driven insights for sustainable agricultural development and food security.
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 , and the obtained experimental results.

1. Introduction

In recent years, the agricultural sector has witnessed a significant transformation propelled by the integration of machine learning (ML) and deep learning (DL) techniques. These technologies have revolutionized traditional farming practices by offering data-driven solutions to age-old challenges faced by farmers and researchers. By leveraging historical data, sensor technologies, and advanced algorithms, ML and DL models have demonstrated remarkable capabilities in various agricultural tasks such as yield prediction, pest and disease detection, crop classification, and resource optimization.

The emergence of ML algorithms like support vector machines (SVM), random forests (RF), and neural networks has enabled precise yield prediction models, empowering farmers to make informed decisions regarding crop management practices, irrigation schedules, and fertilization strategies. On the other hand, DL algorithms such as convolutional neural networks (CNN) and recurrent neural networks (RNN) have showcased unparalleled accuracy in detecting pests, diseases, nutrient deficiencies, and other anomalies affecting crop health.

Additionally, ML and DL technologies play a crucial role in crop classification and weed management, facilitating precision agriculture practices that minimize environmental impact and maximize productivity. Despite the remarkable progress, challenges such as data quality, model interpretability, and scalability remain areas of focus for researchers and practitioners in the field.

This review aims to delve into the extensive applications of ML and DL models in agriculture, highlighting their contributions, challenges, and future prospects. By exploring the latest advancements and innovative use cases, this review seeks to provide insights into how ML and DL continue to shape the future of sustainable and efficient agriculture.

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.

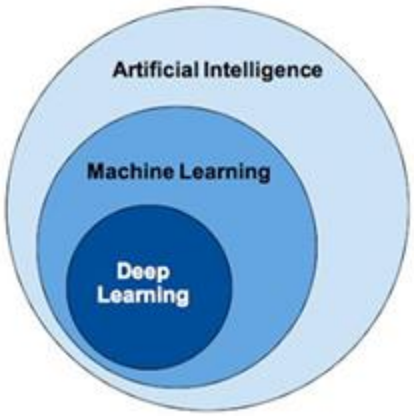

Figure 1. *Relationship between DL and ML*

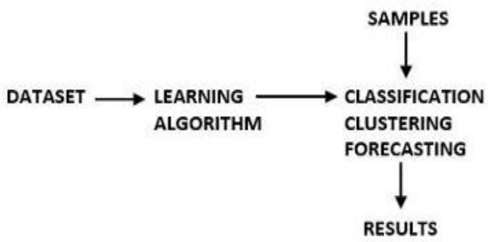

Figure 2. *Machine Learning Architecture* 4.

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.

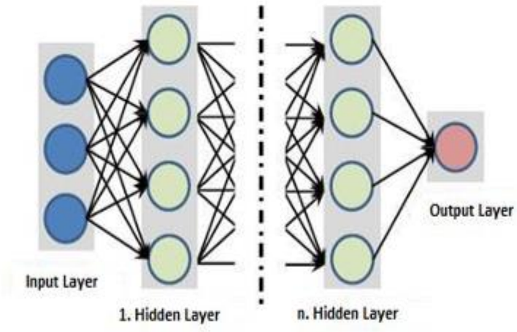

Figure 3. *Deep Learning Architecture*

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, R2, 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.

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)

References.

[1] Avinash, C. Tyagi, Towards a second green revolution. Irrigation and Drainage, 2016. 65(4): p. 388-389.

[2] Elmas, Ç., Yapay Zekâ Uygulamaları [Artificial Intelligence Applications], Turkey: Seçkin Yayınları, 2016, s. 21.

[3] Goodfellow, I., Bengio. Y. and Courville, A., Deep Learning [Cited 2021, 9 April]; Available from: https://www.deeplearningbook.org/

[4] Gülgönül, A. and Akiş, E., Sınır Ötesi Tarım Yatırımlarının Geleceğive Ülkelerin Sınır Ötesi Tarım Yatırımı İhtiyacının espiti İçin Bir Yaklaşım. Atatürk Üniversitesi İktisadi vedari Bilimler Dergisi, 2020. 34 (2): p. 531-553.

[5] Kaya, U., Yılmaz, A. and Dikmen, Y., Sağlık alanında kullanılan derin öğrenme yöntemleri. European Journal of Science and Technology, 2019. 16: p. 792-808.

[6] Liakos, K. G., Busato, P., Moshou, D., Pearson, S. and Bochtis, D., Machine Learning in Agriculture: A Review.Sensors, 2018. 18(8): p. 2674.

[7] Michael, S., Ronay, A. and Thomas, H., A survey of the advancing use and development of machine learning in smart manufacturing. Journal of Manufacturing Systems, 2018. 48: p. 170-179.

[8] Mitchell, T. M., Machine learning, McGrawHill, [Cited 2021, 9 April]; Available from: http://www.cs.cmu.edu/~tom/

[9] Nabiyev, V. V., Yapay Zekâ [Artificial Intelligence], Turkey: Seçkin Yayınları, 2016, s. 25. (In Turkish).

[10] Oleron, P., Zekâ [L'Intelligence], İletişimYayınları/Çeviri[Translator] – Ela Güngören, 1996, s. 26. (In Turkish)