4th Intercontinental Geoinformation Days

igd.mersin.edu.tr

# Applications of machine learning and deep learning techniques in smart agriculture: A review

**Mehran Dadashzadeh*[1], Kosar Sakhaeian [2]**

[1]University of Tabriz, Faculty of Civil Engineering, Department of Water Resources Engineering, Tabriz, Iran
[2]University of Tabriz, Faculty of Planning and Environmental Sciences, Department of Urban Planning, Tabriz, Iran

**Keywords**
Smart agriculture
Machine learning
Deep learning
Land cover identification
Diseases management

**Abstract**

Smart farming is a novel concept that makes agriculture more productive by employing up-to-date information technologies. The most recent developments in automation and artificial intelligence empower farmers better to monitor all procedures and exert accurate treatments determined by machines with great precision. Farmers, experts and data scientists keep on dealing with techniques that allow for optimizing the human labor required in farming. Machine Learning (ML) and Deep Learning (DL) networks that do not need human intervention while performing automatic feature extraction have a significant advantage over previous algorithms. ML and DL allow performing continuous decision-making based on data analysis. Nowadays these techniques have been applied in many applications of smart agriculture such as land cover identification, crop disease detection, weeds removal, and pest recognition. The focus of this study is to review the potential of using ML and DL techniques in agricultural applications and focus on how they are used for smart agriculture.

## 1. Introduction

Agriculture ensures food security for the country that's why it is the backbone of the country. It plays a vital role in the external trade of most of the country. In most parts of the world, approximately 75% of people rely on agriculture as a livelihood. Due to the boom in population, farmers are looking for efficient ways to increase crop production with less expense and efficient utilization of available resources. This contributes new implementation of digital technologies in the agriculture field to help the farmers to make better decisions and increase yields. Nowadays artificial intelligence techniques are utilized to overcome various problems and challenges in agriculture fields (Dhayabarani et al. 2018). Therefore, many researchers have focused on intelligent systems that monitor and control agricultural parameters by increasing productivity and efficiency. Intelligent systems collect data for measurements and get accurate results that can take the appropriate action. The most common subsets of artificial intelligence, Machine Learning (ML) and Deep Learning (DL), have a considerable potential to handle numerous challenges in the establishment of knowledge-based farming systems (Benos et al. 2021). A vast range of ML and DL applications are also existing in smart agriculture and farming. Land cover identification, disease management and weed management are a few examples of the application of these techniques in this field. This study aims at shedding light on ML and DL applications in agriculture by reviewing the recent scholarly literature. it is expected that the present study will constitute a lucrative guide towards enhancing awareness of the potential benefits of using artificial intelligence techniques in agriculture and contributing to more structured research on this issue.

## 2. General Considerations on Machine Learning and Deep Learning

Artificial intelligence (AI) includes several tools and algorithms to computationally imitate human intelligence. AI might use various algorithms derived from the subfields of ML or DL to push forward the computerization of human experts' tasks.

Overall, ML aims at generating informed evaluations by detecting relationships in information employing numerical algorithms, with these procedures presenting the advantage of being able to computerize the method of hypothesis construction. ML algorithms have integrated and, in some instances, modified the

* **Corresponding Author**

*(mehrandadashzadeh@tabrizu.ac.ir) ORCID ID 0000– 0001– 9521– 7330
(k.sakhaeian31@gmail.com) ORCID ID 0000– 0002– 7983– 8441

**Cite this study**

Dadashzadeh, M., & Sakhaeian, K. (2022). Applications of machine learning and deep learning techniques in smart agriculture: A review. 4th Intercontinental Geoinformation Days (IGD), 229-232, Tabriz, Iran

conventional statistical methodologies (Lynch and Liston 2018).

DL is a subfield of ML enthused by the configuration of the brain relying on the so-called artificial neural networks (ANNs). Basically, it structures algorithms into layers in order to create ANNs, able to learn and take an intelligent decision on their own (Deng and Yu 2014).

## 3. Machine Learning and Deep Learning Applications in Smart Agriculture

ML and DL could be considered as novel ways for machines to simulate human learning activities, gain new knowledge, continually improve performance, and achieve unique maturity. In the past few years, these techniques have been very successful in algorithms, theories, and applications, combined with other agricultural techniques to minimize crop costs and maximize yield. ML and DL applications on agricultural farms can be widely used in areas such as land cover identification, disease detection, crop detection, weed detection, soil conditions, crop quality, weather forecasting, etc. The most prominent areas are reviewed in more detail below.

### 3.1. Land Cover Identification

Land cover and crop type maps have emerged as an area where ML and DL could be used efficiently. Several studies used these techniques for land productivity assessment and land cover classification. Kussul et al. (2019) presented a workflow for developing sustainable goals indicators assessment using high-resolution satellite data. Persello et al. (2019) combined a full CNN with globalization and grouping to detect field boundaries. Zhou et al. (2019) presented a DL-based classifier that learns time-series features of crops and classifies parcels of land. Using these parcels, a final classification map was produced. Zhao et al (2019) proposed a method for rice mapping which combined a decision tree method and a CNN model.

### 3.2. Diseases Management

In agriculture, it is critical to monitor the condition of the products and to control the spread of diseases. ML and DL techniques can be used to identify and manage diseases in agricultural fields. ML methods further stimulate appropriate pesticides to protect crops from these infections and reduce labor. Such a system assists producers by obtaining statistics and planning fertilizers, pesticides, and irrigation accordingly. For instance, by accurately identifying the disease and providing accurate pesticide application and irrigation schemes, grape visibility and volume have been increased and extreme pesticide use reduced (Adedoja et al. 2019). Fuentes et al. (2017) introduced a DL-based detector for recognizing diseases and pests in tomato plants. Kerkech et al. (2018) proposed DL approaches for vine disease detection using vegetation indices and colorimetric spaces, applied to images collected by UAV. A low shot learning method for disease identification in tea leaves was proposed by Hu et al. (2019). Coulibaly et al. (2019) suggested an approach for the identification of mildew disease in pearl millet, which is using transfer learning with feature extraction. An artificial intelligence-based approach for detecting grapevine yellows symptoms was proposed by Cruz et al. (2019). Picon et al. (2019) proposed a deep convolutional neural network-based approach for crop disease classification on wheat images.

### 3.3. Weed Management

Ever since humans first attempted the cultivation of plants, they have had to fight the invasion by weeds into areas chosen for crops. Weed recognition is one of those essential that requires digitization and automation. Therefore, data-driven and image processing-based techniques need to be developed. In recent years, various studies have been carried out for the automation of the process of identification and classification of weeds. Tang et al. (2017) proposed a new approach that combined CNN and K-means feature learning for weed identification and control. The application of DL and K-means pre-training resulted in an accuracy of identification of 92.89%. Santos Ferreira et al. (2017) used CNN to perform weed detection in soybean crop images and classify them as grass and broadleaf weeds. Moshia and Newete (2019) proposed a DL neural network, for the automatic identification of weeds from the main crop using row-guided robots. Bah et al. (2018) proposed a learning method using CNN for weed detection from images collected by UAV that automatically performed unsupervised training dataset collection. Kounalakis et al. (2019) combined a classifier for weed recognition with transfer learning techniques for DL-based feature extraction. Partel et al. (2019) developed a smart sprayer using machine vision and artificial intelligence. This smart sprayer distinguishes target weeds from crops and precisely sprays the targeted weed. Subeesh et al. (2022) investigated the feasibility of DL-based techniques in weed identification from RGB images of bell pepper fields.

### 3.4. Pest Recognition

Pest attack is one of the significant problems in the agriculture sector that results in the degradation of crop quality. These destructive insects, known as agricultural pests, need to be correctly identified and treated according to their species to minimize the damage they cause. Recently, many developments have been made in the agriculture sector, using ML and DL techniques to detect and classify insects under stored grain conditions. Cheng et al. (2017) performed pest identification via deep residual learning in a complex background. Ding and Taylor (2016) proposed an automatic detection pipeline based on DL for identifying and counting pests in images taken inside field traps. Shen et al. (2016) exerted a deep neural network for the detection and identification of stored-grain insects. Partel et al. (2019) used artificial intelligence to develop an automated vision-based system that can be utilized for monitoring pests, such as the Asian citrus psyllid. Li et al. (2019) proposed an effective data augmentation strategy for CNN-based pest recognition and localization in the field.

Kasinathan et al. (2021) presented the insect pest detection algorithm that consists of foreground extraction and contour identification to detect the insects in a highly complex background. They used different shape features for insect classification by applying ANN, SVM, KNN, NB, and CNN models.

## 4. Conclusion

Due to the population growth in the world, there is a great demand for agricultural products. That's why it is necessary to increase the production in agriculture. Nowadays the latest technologies such as ML and DL are used to increase agriculture production, reduce production costs and increase income. Applying ML algorithms to data generated from various inputs from farms can make the system smarter and provide definitive information and make predictions.

The focus of the present study is to identify where ML and DL techniques have been used for improving various agricultural practices. Applications of these techniques in the most prominent areas of agriculture are reviewed in this study. It is anticipated that the present review motivates more researchers to focus on AI topics, related to data analysis, image analysis and computer vision, applying it for classification or prediction in smarter farming.

## References

Adedoja, A., Owolawi, P. A., & Mapayi, T. (2019). Deep Learning Based on NASNet for Plant Disease Recognition Using Leave Images, International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD), Winterton, South Africa, 1-5.

Alvarez-Gila, P., Seitz, M., Ortiz-Barredo, A., Echazarra, J., Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild, Computers and Electronics in Agriculture, (161), 280-290.

Bah, M. D., Hafiane, A., & Canals, R. (2018), Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. Remote sensing, (10), 16-90.

Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine Learning in Agriculture: A Comprehensive Updated Review, Sensors (Basel), (21): 37-58.

Cheng, X., Zhang, Y., Chen, Y., Wu, Y., & Yue, Y. (2017). Pest identification via deep residual learning in complex background, Computers and Electronics in Agriculture, (141), 351-356.

Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., & Traore, D. (2019). Deep neural networks with transfer learning in millet crop images. Computers in Industry, (108), 115-120.

Cruz, A., Ampatzidis, Y., Pierro, R., Materazzi, A., Panattoni, A., De Bellis, L., & Luvisi, A. (2019). Detection of grapevine yellows symptoms in Vitis vinifera L with artificial intelligence. Computers and electronics in agriculture, (157), 63-76.

Deng, L., & Yu, D. (2014), Deep learning: methods and applications: Foundations and Trends in Signal Processing, (7), 197-387.

Dhayabarani, A., Aravinth, K., Gowtham, M., Gowtham, D., & Balakrishnan, (2018), Detection of Weed using Neural Networks. International Journal of Engineering Research and Technology, (6), 1-5.

Dimitriadis, S., & Goumopoulos, C. (2008). Applying Machine Learning to Extract New Knowledge in Precision Agriculture Applications, Panhellenic Conference on Informatics, Samos, 100-104.

Ding, W., & Taylor, G. (2016), Automatic moth detection from trap images for pest management, Computers and Electronics in Agriculture, (123),17-28.

Ferreira, d. S., Freitas, D. M., da Silva, G. G., Pistori, H., Folhes, M. T. (2017). Weed detection in soybean crops using ConvNets. Computers and Electronics in Agriculture, (143), 314-324.

Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests' recognition, Sensors, (17), 1-21.

Fyfe, C. (2000), Artificial Neural Networks and Information Theory, Department of Computing and Information System, The university of Paisley, Paisley, UK.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning, USA: MIT Press, 1-15.

Hu, G., Wu, H., Zhang, Y., & Wan, M. (2019). A low shot learning method for tea leaf's disease identification, Computers and Electronics in Agriculture, (163), 104-852.

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey, Computers and Electronics in Agriculture, (147), 70–90.

Kasinathan, T., Singaraju, D., & Reddy, S. (2021), Insect classification and detection in field crops using modern machine learning techniques, Information Processing in Agriculture, (8), 446-457.

Kavitha, A. (2021). Deep Learning for Smart Agriculture. International Journal of Engineering Research & Technology (IJERT), (9), 132-134.

Kounalakis, T., Triantafyllidis, G. A., & Nalpantidis, L. (2019). Deep learning-based visual recognition of rumex for robotic precision farming, Computers and Electronics in Agriculture, (165), 104-973.

Kerkech, M., Hafiane, A., & Canals, R. (2018). Deep leaning approach with colorimetric spaces and vegetation indices for vine diseases detection in UAV images, Computers and electronics in agriculture, (155), 237-243.

Kussul, N., Lavreniuk, M., Kolotii, A., Skakun, S., Rakoid, O., & Shumilo, L. (2019). A workflow for Sustainable Development Goals indicators assessment based on high-resolution satellite data, International Journal of Digital Earth, 1-13.

Li, R., Wang, R. R., Zhang, J., Xie, C., Liu, L., Wang, F., Chen, H., Chen, T., Hu, H., X, J., Hu, M., Zhou, M., Li, D., & Liu, W. (2019). An Effective Data Augmentation Strategy for CNN-Based Pest Localization and Recognition in the Field, (7), 274-283.

Lynch, C. J., Liston, C. (2018). New machine-learning technologies for computer-aided diagnosis, Nat. Med, (24), 1304–1305.

Maduranga, P., & Abeysekera, R. (2020). Machine learning application in IoT base agriculture and smart framing: A Review, International Journal of Engineering Applied Sciences and Technology, (4), 24-27.

Mahdavinejad M S et al (2018), Machine learning for internet of things data analysis: a survey in proc, Digital Communications and Network, 161–175.

Medela, et al (2013), IoT Multiplatform networking to monitor and control wineries and vineyards, Future Network and Mobile Summit, 1–10.

Moshia, M. E., Newete, S. W. (2019). Mexican poppy (Argemone mexicana) control in cornfield using deep learning neural networks: a perspective, Acta Agriculturae Scandinavica, Section B-Soil and Plant Science, (69), 228-234.

Partel, V., Kakarla, S. C., & Ampatzidis, Y. (2019). Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence, Computers and electronics in agriculture, (157), 339-350.

Partel, V., Nunes, L., Stansly, P., & Ampatzidis, Y. (2019). Automated vision-based system for monitoring Asian citrus psyllid in orchards utilizing artificial intelligence. Computers and Electronics in Agriculture, (162), 328-336.

Persello, C., Tolpekin, V. A., Bergado, J. R., de By, R. A. (2019). Delineation of agricultural fields in smallholder farms from satellite images using fully convolutional networks and combinatorial grouping, Remote sensing of environment, (231), 111-253.

Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019), Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild, Computers and Electronics in Agriculture, (161), 280-290.

Popa, M., Prostean, O., & Popa, A. S. (2019). Machine Learning Approach for Agricultural IoT in Proc. International Journal of Recent Technology and Engineering (IJRTE), 22-29.

Raschka, S., & Mirjalili, V. (2017). Machine Learning and Deep Learning with Python. scikit-learn and TensorFlow, Birmingham, İngiltere: Packt Publishing, 2-6.

Santos Ferreira, A., Freitas, D. M., da Silva, G. G., Pistori, H., & Folhes, M. T. (2017). Weed detection in soybean crops using ConvNets, Computers and Electronics in Agriculture, 314-324.

Shakoor, M. T., Rahman, K., Rayta, S. N., & Chakrabarty, A. (2017). Agricultural production output prediction using Supervised Machine Learning Siddique T, Barua D, Ferdous Z, Chakrabarty A (2017), Automated farming prediction. Intelligent Systems Conference (IntelliSys), 757-763.

Shen, Y., Zhou, H., Li, J., Jian, F., & Jayas, D. (2018). Detection of stored-grain insects using deep learning. Computers and Electronics in Agriculture, 145, 319-325.

Subeesh, Bhole S, Singh K, Chandel N S, Rajwade Y A, Rao K V R, Kumar S P, Jat D (2022), Deep convolutional neural network models for weed detection in polyhouse grown bell peppers. Artificial Intelligence in Agriculture, (6), 47-54.

Tang, J. L., Wang, D., Zhang, Z. G., He, L. J., Xin, J., & Xu, Y. (2017). Weed identification based on K-means feature learning combined with convolutional neural network, Computers and Electronics in Agriculture, (13), 63–70.

Thenmozhi, Reddy U S (2019), Crop pest classification based on deep convolutional neural network and transfer learning, Computers and Electronics in Agriculture, (164), 104-906.

Techniques, 1st International Conference on Next Generation Computing Applications (NextComp), Mauritius, 182-187.

Ünal, Z. (2020). Smart Farming Becomes Even Smarter with Deep Learning: A Bibliographical Analysis, IEEE Access, (8), 105587 – 105609.

Varman, S. A. M., Baskaran, A., Baskaran, A. R., & Prabhu, E. (2017). International Conference on Computational Intelligence and Computing Research (ICCIC).

Zhu, N., Liu, X., Liu, Z., Hu, K., Wang, Y., Tan, J., Huang, M., Zhu, Q., Ji, X., Jiang, Y., Guo, Y. (2018). Deep learning for smart agriculture: Concepts, tools, applications, and opportunities. International Journal of Agricultural and Biological Engineering, (11), 32-44.

Zhou, Y. N., Luo, J., Feng, L., Yang, Y., Chen, Y., & Wu, W. (2019). Long-short-term memory-based crop classification using high-resolution optical images and multi-temporal SAR data, GIScience and Remote Sensing, (56), 1170-1191.

Zhao, S., Liu, X., Ding, C., Liu, S., Wu, C., & Wu, L. (2019). Mapping Rice Paddies in Complex Landscapes with Convolutional Neural Networks and Phenological Metrics. GIScience & Remote Sensing, 1-12.