Applications of smart agriculture for environmental protection using deep learning techniques

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Abstract. DL, short for Deep Learning, is a cutting-edge approach that merges advanced techniques in image processing and data analysis with the power of big data analysis. Its potential is enormous and has already found practical applications in several fields, including autonomous driving, automatic speech recognition, medical research, image restoration, natural language processing, and, among others. DL has been recently introduced in agriculture showing promising results in solving various farming problems like disease detection, automated plant and fruit identification, and counting. This study presents a comprehensive review of research using DL techniques in farming, including crop monitoring, crop mapping, weed and pest detection and management, irrigation, fruit grading, reorganizations of species and herbicide identification. Furthermore, different DL techniques applied in various fields are analyzed and compared with existing techniques. It was found that DL outperforms traditional image processing technology in terms of accuracy, both in classification and regression. Additionally, the study suggests that DL can be applied beyond detections, classification tasks to yield production, and disease segmentation in agriculture.

Index Terms— Deep learning, Techniques, Smart Agriculture, CNN, ANN, Environment, Survey.

1. Introduction

In numerous countries, agriculture is recognized as a crucial sector that bears considerable economic influence. With the expanding population [1], ensuring food sufficiency has become a major apprehension. Consequently, shifting to smarter farming methods has become imperative in attaining food security goals. Recently, there has been extensive research on DL techniques like Recurrent Neural Networks and Convolutional Neural Networks, which have found widespread application in diverse fields, including agriculture. [2]

Farmers, data scientists, and engineers are working together to perfect methods of optimizing human work in agriculture. With the constant improvement of information sources, smart agriculture is evolving into a machine learning system that is becoming increasingly advanced [3]. DL is a form of ML that relies on ANN. What sets them apart from ordinary neural networks is their depth, which allows them to discover hidden structures in unlabeled and unemitted data. A significant benefit of modern deep learning networks is their ability to automatically extract features without the need for human intervention, which sets them apart from earlier algorithms.

Moreover, it is possible to boost production and decrease expenses while simultaneously decreasing pollution levels. The timely detection and prevention of crop diseases [4] can effectively impede their spread. Additionally, by preemptively utilizing fewer pesticides, pollution levels can be diminished. The provision of precise and prompt crop information is vital for social, economic, and environmental welfare.

The objective of this article is to explore the latest advancements in smart agriculture systems that leverage techniques of deep learning. The author's motivation for undertaking this study is based on the significance of DL applications in addressing agricultural issues through innovative solutions. While the adoption of DL techniques in smart agriculture is still in its nascent stages, it has become increasingly popular in recent publications. Thus, the author emphasizes the role of DL techniques in solving intelligent agriculture problems related to decision-making and data processing.

2. Methodology

In recent years, the field of smart agriculture has experienced significant growth in various domains, with deep learning applications being widely embraced and delivering impressive and gratifying results. This research endeavor seeks to furnish a contemporary and all-encompassing resource for scholars by scrutinizing and exploring the employment of deep learning techniques in agriculture.

This review is based on two primary steps: first, a search for recent works published within the last five years, and second, a review and analysis of the selected works. The search for related works was carried out between March and May 2022 using primarily Google Scholar. The research was not restricted to any particular method of deep learning, and 55 articles were initially selected from different agricultural domains. After thorough examination, we further refined the selection and narrowed it down to 23 papers that carried DL experiments and presented their outcomes.

3. A brief introduction to Deep Learning

DL is a subset of machine learning that involves the use of ANN to learn from large amounts of data. These neural networks are composed of multiple layers of interconnected artificial neurons that work together to learn from large datasets and make accurate predictions [5]. It has become increasingly popular in recent years due to its ability to solve complex problems that were previously difficult or impossible to solve with traditional machine learning algorithms. Some common applications of deep learning include autonomous vehicles, image recognition, recognizing speech and natural language processing. [33]

The success of DL is largely due to its ability to automatically learn features and representations from raw data, without the need for hand-designed features or domain-specific knowledge. This makes it well-suited for tasks where traditional methods struggle, such as image and speech recognition. Training and optimizing complex models in deep learning necessitates vast amounts of labeled data and high-performance computing resources like GPUs [34]. However, the increased availability of cloud computing and Big Data has simplified the development and deployment of deep learning applications in recent times.

Deep learning models are derived by the function and structure of the human brain, where each layer of the neural network processes a specific level of abstraction of the input data. In order to train a deep learning algorithm, a vast amount of data is

This is accomplished by adjusting the parameters of the algorithm in a way that enhances its accuracy and predictive capabilities.

Artificial Neural Network

An artificial neural network (ANN) is a deep learning algorithm that is inspired by the structure and function of the human brain to process data. ANN architecture refers to the way artificial neurons are organized and interconnected to process input information and produce output. The ANN architecture are designed with multiple layers of interconnected nodes, each serving a distinct purpose [35]. The initial input layer receives data, while the final output layer generates the model's output. Sandwiched between these two layers are hidden layers, which execute a series of intermediate computations to process the input data into the desired output. By organizing neurons into layers and processing data hierarchically, ANNs can tackle complex problems and generate highly accurate predictions.

Each neuron in an artificial neural network is connected to all neurons in the previous and next layers. Each connection is associated with a weight that can be adjusted during training to improve the performance of the network. The training process consists of iteratively adjusting the weights using an optimization algorithm to reduce a cost function that measures the error between the predicted output and the actual output. Once the model is trained, it can be used to predict the output for new input data.

There are different architectures of ANN, such as recurrent neural networks, convolutional neural networks and feed forward neural networks, which are optimized for specific tasks such as speech recognition, image classification and sequence prediction.
Figure 1 displays a basic neural network that comprises three parts, namely (i) the input layer, (j) hidden layer, and (k) output layer.

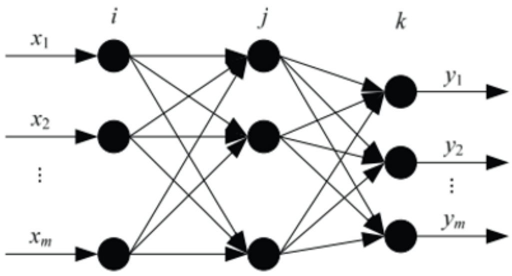

Figure 1 : ANN Architecture [30]

Convolutional Neural Network

Convolutional Neural Networks (CNN) [35], a DL algorithm, utilizes a deep feed forward ANN and is equipped with shared weights, advanced layering capabilities, and exceptional learning ability. These features enable CNN to effectively tackle complex problems with larger models and generate impressive outcomes. In fact, CNN has made significant strides in various applications, including speech recognition, language translation, image recognition, and information retrieval. However, when it comes to solving large-scale issues, CNN is not as proficient as ANN.

CNNs are a type of neural network particularly suited to processing images and other two-dimensional data. The architecture of a CNN typically consists of several layers, including a convolution layer, an activation layer, a pooling layer, a fully connected layer and possibly a dropout layer. Figure 2

The convolution layer is the first layer of a CNN. In this layer, the input image is convolved with a set of learnable filters, which detect different features like edges, corners and shapes. The output of this layer is a set of feature maps.

After the convolution layer, an activation layer is usually added. This layer applies a nonlinear function to the output of the convolution layer, allowing the network to learn more complex features.
The pooling layer is used to minimize the spatial size of the activation layer output, while retaining the most important information. This layer can help Decrease the number of parameters in the network, making it faster and more efficient.

in traditional neural networks and can be used for tasks such as classification or regression.

Finally, a dropout layer can be added to the network to avoid overlearning. This layer randomly removes a certain percentage of neurons in the network during training, compelling the model to identify more resilient features in the data.

Overall, the architecture of CNNs is designed to allow the network to learn hierarchical representations of the input data, with each layer building on the previous one to learn increasingly complex features [36]. This makes CNNs particularly suited to tasks E.g. object detection and image classification.

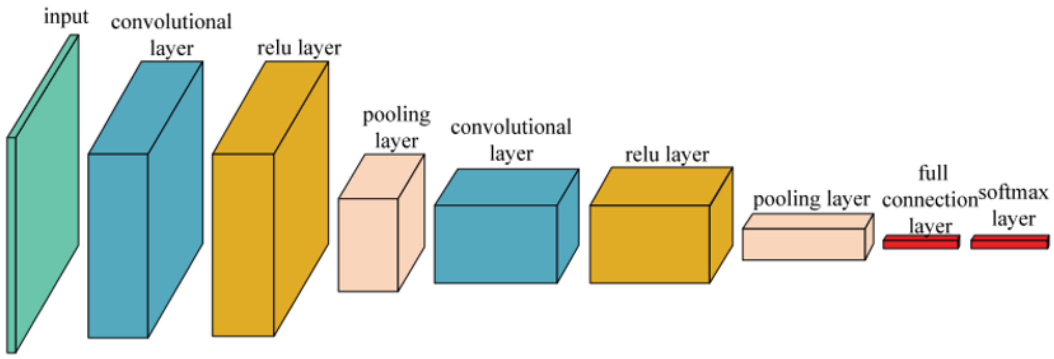

Figure 2: CNN Architecture. [29]

4. Application of DL in agriculture

Smart agriculture is utilizing deep learning algorithms to monitor a range of parameters that can be observed from anywhere globally. Previous surveys have mostly examined the advantages of DL in specific agricultural applications. However, our overview offers an examination of deep learning's contributions to various smart agriculture applications. We analyzed which deep learning models were most suitable and effective for different applications. Our findings indicate that researchers are increasingly interested in using the Convolutional Neural Network (CNN) algorithm for classification applications and plant disease detection, which has produced remarkable results.

The CNN algorithm is commonly utilized in weather forecasting applications due to its ability to analyze time series data and deliver accurate outcomes. In our research, we examined the diverse domains of smart agriculture where deep learning techniques are employed, and we have compiled our discoveries in Table 1.

Deep learning has a lot of potential applications in agriculture. Here are some examples:

Crop Yield Prediction: considered to be one of the most notable applications of deep learning in the field of agriculture [37]. DL algorithms can analyze large datasets of historical weather data, soil quality, crop type, and other factors to predict crop yields accurately. This can help farmers optimize their crop management practices, leading to increased yields and reduced costs.

Disease Detection: Deep learning algorithms can analyze images of plants to detect diseases accurately [38]. By training deep learning models on large datasets of plant images, researchers can develop models that can accurately identify diseases and provide recommendations for treatment.

Soil Analysis: Deep learning algorithms can analyze soil samples to provide information about soil quality and nutrient content. By analyzing large datasets of soil samples, deep learning models can identify patterns and predict soil properties accurately[39].

learning models on large datasets of field images, researchers can develop models that can accurately identify weeds and recommend the best course of action for their removal.

Table 1

Ref	Agriculture Area	Problem Description	Dataset	DL Model	Framework	Results
[6]	Weather forecasting	Frost prediction in crops by estimating low temperatures	Data time series IoT infrastructure generates 144 rows per day	LSTM	Keras TensorFlow	RMSE 0.8068
[7]	Identification of water	Monitoring of stress induced by water deficiency in plants	The authors created a new dataset of two chickpea varieties, JG62 and Pusa372, containing 7680 images	CNNLSTM	TensorFlow and Keras	Accuracy 98.52% on JG-62 chickpea plant data Accuracy 97.78% on Pusa-372 chickpea plant data
[8]	Identification of weeds	Weed Classification from Natural Corn Field	Collected by authors	CNN	Tensorflow	Accuracy 97%
[9]	Identification of weeds	Recognize weeds and identify their growth stages	(Public dataset). The dataset consists of 9649 images for various types of weeds, divided into nine classes	Pytorch	RMSE 0.8068	Accuracy 93.45%
[10]	Crop identification/ classif ication Plant	Plant detection and density variation	Collected by authors	FRCNN		
[11]	crop identification/ classification	Fruit quality classificatio	Collected by authors	R-CNN		Accuracy 97.86%
[12]	crop identification /classification	Classification to differentiate crops, soils, and weeds as well as individual weed species	The dataset used in this study was an independent image set with 16,500 image patches	ResNet-18 DCNN classifie	TensorFlow	Accuracy 94%
[13]	Identification/classif ication of plant disease	Detection of tomato plant diseases	PlantVillage dataset	VGG19 AlexNet		Accuracy 98.9%
[14]	Identification/classif ication of plant disease	Detection of tomato plant diseases	Tomato leaf diseases dataset in AI CHALLENG ER	Restructur ed residualdense network	Developed by the author	Accuracy 95%
[15]	Identification/classif ication of plant disease	Detection of tomato plant diseases	PlantVillage dataset	Segmentat ion-based CNN	Developed by the author	Accuracy 98.49
[16]	Pig counting	Automatic counting and positioning of slaughter pigs	In a real environment	Counting CNN	caffe	1.67 MAE per image

5. Discussion

In order to meet the food demands of the world's rapidly increasing population, it is imperative to update the agricultural sector with cutting-edge technologies. The use of modern technologies with high efficiency is particularly crucial due to the growing environmental issues negatively impacting this sector [31].

Smart agriculture [32] is a broad field encompassing diverse areas, data collection, including sensor development, network maintenance, and artificial intelligence-based decision-making. Over the past two decades, the emergence of AI and DL has significantly contributed to the growth of projects in this field. In particular, deep learning techniques have demonstrated remarkable performance compared to conventional methods in the majority of related work.

to make decisions, certain crucial factors that can impact these decisions are frequently disregarded. crop standard procedures, weather predictions, farmer feedback, historical crop data, and government regulations are not taken into account in the decision-making process.

Advantage and Disadvantage of DL in agriculture

DL offers several advantages and disadvantages in the field of agriculture. In terms of advantages, deep learning can be used to improve crop production and quality by allowing for accurate soil and crop analysis and yield prediction. Deep learning models can also help identify diseased plants or weeds, allowing for more efficient crop management. In addition, deep learning can help optimize the use of resources such as water, fertilizers and pesticides, which can reduce production costs and minimize environmental impacts.

However, there are also drawbacks to using deep learning in agriculture. First, DL models require high quality and large amounts of data to be accurate. Collecting this data can be costly and time-consuming, especially in rural areas where access to digital technologies may be limited. In addition, deep learning models can be difficult to interpret, which can pose decision-making challenges for farmers. Finally, deep learning models can be expensive to implement and maintain, often requiring specialized skills and resources.

In conclusion, deep learning can offer many benefits for agriculture, but it is important to consider the potential drawbacks before adopting it in this field. Farmers should carefully evaluate the benefits and costs of using deep learning models and be aware of the challenges they may face when implementing them.

Future of DL in agriculture

Due to the varying climatic conditions, nature, and features across regions, agriculture is a complex field that requires technology to identify and analyze elements of interest from collected data. This involves handling large amounts of real-time data, which is where deep learning technology comes into play, utilizing algorithms E.g. CNN and RNN. By processing field data on soil types, climate parameters, weather patterns, and other factors, a deep learning algorithm can build a probabilistic model to identify diseases in plants and track changes in weather patterns [41]. The advantage of DL is that it can create selected features without human intervention through unsupervised learning, making it well-suited for the constantly changing real-time environment of agriculture. This is particularly important as the Internet of Things (IoT) [42] continues to generate unclassified and unstructured data, where DL models outperform traditional methods like SVM, RF ,and ANN in terms of automatic feature extraction efficiency.

6. Conclusion

In this study, a comprehensive overview of DL research in agriculture is presented. The paper investigates several agricultural domains, identifies the problems addressed, specifies technical aspects such as the DL model and architecture, describes the data sources utilized, reports the accuracy of each study relative to conventional methods, evaluates the hardware utilized, and considers potential real-time applications. The findings reveal that DL has demonstrated high accuracy across most of the reviewed studies, surpassing the precision of traditional methods.

The main advantage of non-DL techniques is the shorter classification time, allowing for easier real-time implementation. However, the hardware requirement for DL, primarily powerful GPUs with high power consumption, can be a significant disadvantage. Although there are alternative, low-power systems such as FPGAs, they have not yet been extensively explored in the agricultural domain. To integrate DL techniques with autonomous robotic platforms (AGVs) in real-time, further research is required to reduce the complexity and hardware demands of existing effective DL methods.

[1] Kitzes, J.; Wackernagel, M.; Loh, J.; Peller, A.; Goldfinger, S.; Cheng, D.; Tea, K. Shrink and share humanity's present and future ecological footprint. Philos. Trans. the Roy. Soc. Lond. B Biol. Sci. 2008, 363, 467–475.

[2] Kamilaris, A.; Prenafeta-Boldú, F.X. Deep learning in agriculture: A survey. Comput. Electron. Agric. 2018, 147, 70–90.

[3] Liu, Q.; Yan, Q.; Tian, J.; Yuan, K. Key technologies and applications in intelligent agriculture. J. Phys. Conf. Ser. 2021, 1757, 012059.

[4] Strange, R.N.; Scott, P.R. Plant disease: A threat to global food security. Annu. Rev. Phytopathol. 2005, 43, 83–116.

[5] A. S. Lundervold and A. Lundervold, "An overview of deep learning in medical imaging focusing on MRI," *Z. Med. Phys.*, vol. 29, no. 2, pp. 102–127, 2019, doi: 10.1016/j.zemedi.2018.11.002.

[6] Guillén, MA; Llanes, A.; Imbernon, B.; Martínez-España, R.; Bueno-Crespo, A.; Cano, JC; Cecilia, JM Évaluation des performances des plates-formes informatiques de pointe pour la prédiction des basses températures en agriculture à l'aide de l'apprentissage en profondeur. J. Supercalculateur. 2021 , 77 , 818–840.

[7] Azimi, S.; Wadhawan, R.; Gandhi, TK Surveillance intelligente du stress induit par le manque d'eau chez les plantes à l'aide de l'apprentissage en profondeur. IEEE Trans. Instrument. Mes. 2021 , 70 , 5017113.

[8] Garibaldi-Marquez, F.; Flores, G.; Mercado-Ravell, DA ; Ramírez-Pedraza, A.; Valentín-Coronado, LM Classification des mauvaises herbes à partir d'images de champs de maïs naturels multi-plantes basée sur l'apprentissage superficiel et profond. Capteurs 2022 , 22 , 3021.

[9] Mhango, JK; Harris, EW ; Vert, R. ; Monaghan, JM Cartographie de la variation de la densité des plants de pommes de terre à l'aide d'images aériennes et de techniques d'apprentissage en profondeur pour l'agriculture de précision. Remote Sens. 2021 , 13 , 2705.

[10] Mohapatra, D.; Choudhury, B.; Sabat, B. Un système automatisé pour la gradation des fruits et la localisation des aberrations à l'aide de l'apprentissage en profondeur. Dans Actes de la 7e Conférence internationale 2021 sur les systèmes informatiques et de communication avancés (ICACCS), Coimbatore, Inde, 19-20 mars 2021.

[11] de Camargo, T.; Schirrmann, M.; Landwehr, N.; Dammer, KH; Pflanz, M. Modèle d'apprentissage en profondeur optimisé comme base pour la cartographie rapide par UAV des espèces de mauvaises herbes dans les cultures de blé d'hiver. Remote Sens. 2021 , 13 , 1704.

[12] Kibriya, H.; Abdallah, I. ; Nasrullah, A. Identification et classification des maladies des plantes à l'aide d'un réseau de neurones convolutifs et de SVM. Dans Actes de la Conférence internationale 2021 sur les frontières des technologies de l'information (FIT), Islamabad, Pakistan, 13-14 décembre 2021 ; p. 264–268.

[13] Zhou, C.; Zhou, S.; Xing, J.; Song, J. Identification des maladies foliaires de la tomate par un réseau dense résiduel profond restructuré. Accès IEEE 2021 , 9 , 28822–28831.

[14] Trivedi, NK; Gautam, V. ; Anand, A.; Aljahdali, HM; Villar, SG; Anand, D.; Goyal, N.; Kadry, S. Détection précoce et classification de la maladie des feuilles de tomate à l'aide d'un réseau de neurones profonds à haute performance. Capteurs 2021 , 21 , 7987.

[15] Vypirailenko, D.; Kiseleva, E.; Shadrin, D.; Pukalchik, M. Deep learning techniques for enhancement of weeds growth classification. In Proceedings of the 2021 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Glasgow, UK, 17–20 May 2021.

[16] M. Tian, H. Guo, H. Chen, Q. Wang, C. Long, and Y. Ma, "Automated pig counting using deep learning," Computers and Electronics in Agriculture, vol. 163, article no. 104840, 2019.

using the improved YOLO-V3 model," Computers and Electronics in Agriculture, vol. 157, pp. 417-426, 2019.

[18] Y. Qiao, M. Truman, and S. Sukkarieh, "Cattle segmentation and contour extraction based on Mask R-CNN for precision livestock farming," Computers and Electronics in Agriculture, vol. 165, article no. 104958, 2019.

[19] S. A. Jwade, A. Guzzomi, and A. Mian, "On farm automatic sheep breed classification using deep learning," Computers and Electronics in Agriculture, vol. 167, Article 105055, 2019.

[20] M. K. Saggi and S. Jain, "Reference evapotranspiration estimation and modeling of the Punjab Northern India using deep learning," Computers and Electronics in Agriculture, vol. 156, pp. 387-398, 2019.

[21] Fawakherji, M.; Youssef, A.; Bloisi, D.D.; Pretto, A.; Nardi, D. Crop and Weeds Classification for Precision Agriculture using Context-Independent Pixel-Wise Segmentation. In Proceedings of the Third IEEE International Conference on Robotic Computing (IRC), Naples, Italy, 25–27 February 2019.

[22] Häni, N.; Roy, P.; Isler, V. A Comparative Study of Fruit Detection and Counting Methods for Yield Mapping in Apple Orchards. *J. Field Robot.* **2019**, *37*, 181–340.

[23] Grimm, J.; Herzog, K.; Rist, F.; Kicherer, A.; Töpfer, R.; Steinhage, V. An adaptable approach to automated visual detection of plant organs with applications in grapevine breeding. Biosyst. Eng. 2019, 183, 170–183.

[24] Yu, J.; Sharpe, S.M.; Schumann, A.W.; Boyd, N.S. Deep learning for image-based weed detection in turfgrass. *Eur. J. Agron.* **2019**, *104*, 78–84.

[25] Yang, Q.; Shi, L.; Han, J.; Zha, Y.; Zhu, P. Deep convolutional neural networks for rice grain yield estimation at the ripening stage using UAV-based remotely sensed images. *Field Crop. Res.* **2019**, *235*, 142–153.

[26] Razfar, N., True, J., Bassiouny, R., Venkatesh, V., & Kashef, R. (2022). Weed detection in soybean crops using custom lightweight deep learning models. Journal of Agriculture and Food Research, 8, Article 100308.

[27] Mostafa, A. M., Kumar, S. A., Meraj, T., Rauf, H. T., Alnuaim, A. A., & Alkhayyal, M. A. (2022). Guava Disease Detection Using Deep Convolutional Neural Networks : A Case Study of Guava Plants. Applied Sciences, 12(1), 239.

[28] Tufail, M., Iqbal, J., Tiwana, M. I., Alam, M. S., Khan, Z. A., & Khan, M. T. (2021). Identification of tobacco crop based on machine learning for a precision agricultural sprayer. IEEE access. IEEE-INST ELECTRICAL ELECTRONICS ENGINEERS INC.

[29] L. Alzubaidi et al., Review of deep learning: concepts, CNN architectures, challenges, applications, future directions, vol. 8, no. 1. Springer International Publishing, 2021. doi: 10.1186/s40537-021-00444-8.

[30] L. Alzubaidi et al., Review of deep learning: concepts, CNN architectures, challenges, applications, future directions, vol. 8, no. 1. Springer International Publishing, 2021. doi: 10.1186/s40537-021-00444-8.

[31] M. Altalak, M. A. Uddin, A. Alajmi, and A. Rizg, "Smart Agriculture Applications Using Deep Learning Technologies: A Survey," Appl. Sci., vol. 12, no. 12, 2022, doi: 10.3390/app12125919.

[32] L. Lipper et al., "Climate-smart agriculture for food security," Nat. Clim. Chang., vol. 4, no. 12, pp. 1068–1072, 2014, doi: 10.1038/nclimate2437.

[33] Dargan, S.; Kumar, M.; Ayyagari, M.R.; Kumar, G. A survey of deep learning and its applications: A new paradigm to machine learning. Arch. Comput. Methods Eng. 2020, 27, 1071–1092.

[34] L. Alzubaidi et al., Review of deep learning: concepts, CNN architectures, challenges, applications, future directions, vol. 8, no. 1. Springer International Publishing, 2021. doi: 10.1186/s40537-021-00444-8.

[35] C. Ren, D. K. Kim, and D. Jeong, "A Survey of Deep Learning in Agriculture: Techniques and Their Applications," J. Inf. Process. Syst., vol. 16, no. 5, pp. 1015–1033, 2020, doi: 10.3745/JIPS.04.0187.

 https://doi.org/10.1051/e3sconf/202341601035

[37] T. van Klompenburg, A. Kassahun, and C. Catal, “Crop yield prediction using machine learning: A systematic literature review,” Comput. Electron. Agric., vol. 177, no. July, p. 105709, 2020, doi: 10.1016/j.compag.2020.105709.

[38] T. van Klompenburg, A. Kassahun, and C. Catal, “Crop yield prediction using machine learning: A systematic literature review,” Comput. Electron. Agric., vol. 177, no. July, p. 105709, 2020, doi: 10.1016/j.compag.2020.105709.

[39] J. Padarian, B. Minasny, and A. B. McBratney, “Using deep learning to predict soil properties from regional spectral data,” Geoderma Reg., vol. 16, p. e00198, 2019, doi: 10.1016/j.geodrs.2018.e00198.

[40] Kassou, M. et al., Digital transformation in flow planning: The case of container terminals at a smart port , Journal of Theoretical and Applied Information Technologythis link is disabled, 2021, 99(9), pp. 1966–1976

[41] A. Kamilaris and F. X. Prenafeta-Boldú, “A review of the use of convolutional neural networks in agriculture,” *J. Agric. Sci.*, vol. 156, no. 3, pp. 312–322, 2018, doi: 10.1017/S0021859618000436.

[42] D. Musleh, M. Alotaibi, F. Alhaidari, A. Rahman, and R. M. Mohammad, “Intrusion Detection System Using Feature Extraction with Machine Learning Algorithms in IoT,” J. Sens. Actuator Networks, vol. 12, no. 2, 2023, doi: 10.3390/jsan12020029.