Original Article

A Deep Learning Based Smart Agriculture Technique For An Iot Environment

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Abstract

The application of deep learning strategies to the emerging field of smart agriculture is undergoing rapid development and is gaining increasing levels of interest. The application of deep learning algorithms to the topic of smart agriculture is something that is being explored, however it is quite early in its development. Utilizing Deep Learning in conjunction with Smart Agriculture in order to make the Internet of Things more accessible Deep learning may be able to assist in taking into consideration a variety of characteristics when developing a strategy for harvesting. These characteristics include the type, quality, and pH of the soil; the weather prediction (including temperature, precipitation, humidity, and hours of sunlight); and the schedule for applying fertilizers. For the objectives of this study, datasets of plant leaves, originating from both healthy and ill plants, were gathered for the training, validation, and testing of the CNN model. These datasets were acquired for the purposes of this study. When applied in agriculture for the purpose of identifying and classifying image of plants, the CNN model obtained the greatest attainable degree of accuracy.

Keywords Deep Learning, Agriculture, IoT

1. Introduction

Greenhouses and other climate-controlled structures are becoming an increasingly popular choice among modern farmers for the management of their crops. Either to increase yields or to simulate the ideal growing circumstances of sites that are further away, so that identical items can be produced closer to home, this may be done as a means of doing one of two things. In addition, with the assistance of contemporary monitoring and information technologies such as the Internet of Things (IoT), autonomous robots, and smartphones, we are able to protect agricultural yield and quality from the devastation that can be caused by variations in extreme weather and disease [1].

Technology advancements have made it possible to optimize the automation of precise management, increase crop production, and possibly have a smaller impact on the environment [2]. This has allowed for the collection of data that is extremely accurate on the state of the crops and the formation of sound decisions regarding irrigation, modifications to climate factors, and the enhancement of soil nutrition. The developments in technology that have made it feasible to boost agricultural production have made this possibility a reality, therefore it is now possible to do this. The utilization of technological innovations among agriculturalists and farmers has increased in recent years in response to a demand for increased productivity in greenhouse operations [3].

Farmers can use their cellphones to acquire an accurate image of the management status through statistical analysis, keep a watch on their crops and machinery from a distance, and provide orders to agricultural robots if the robots collect and transmit sensor data over the internet. The Internet of Things makes this kind of thing conceivable (IoT). On the other hand, the level of artificial intelligence (AI) that is currently implemented in agricultural devices and systems is a long way from achieving fully automated operations and management that require only minimal monitoring in order to maximize production while simultaneously accounting for unpredictability and uncertainty [4]. The effective intervention of people, in addition to the integration of a number of different technology, is proving to be very beneficial to the growth of plants in greenhouses.

Intelligence has been highlighted as a significant enabler in the process of increasing the PA economic potential and ecological value, which has been seen as a significant technological difficulty and has been seen as a vital enabler in meeting that challenge. Intelligence has also been highlighted as a significant enabler in the process of increasing the PA economic potential and ecological value. The development of technology based on deep learning has resulted in the provision of an effective way for supporting intelligent management and decision-making across a wide variety of PA-related areas. These areas include autonomous robots for picking and harvesting crops [7], visual crop classification [5], real-time plant disease and pest recognition [6], and monitoring the health and quality of crops while they are being cultivated [8].

Because deep learning algorithms are able to make use of the increased amounts of data that are being produced as a result of an increase in the number of sensors, cameras, and cellphones, the prospects for the future of agriculture are looking quite positive. This is a positive sign for the sector as a whole. Deep learning is a technique that allows computational models to learn representations of data that have numerous layers of abstraction. This can be accomplished through the use of neural networks. The method draws its inspiration from the multi-level visual perception process that takes place in the human brain. This is accomplished by utilizing non-linear modules (such as convolutional layers or memory units) that each transform the representation at one level (beginning with the raw input) into a representation at a slightly more abstract level [9]. This allows for the representation to be at a slightly higher level of abstraction. This enables the representation to exist at a little higher level of abstraction than would otherwise be possible.

Composing a sufficient number of these transformations makes it possible to automatically learn extremely complex functions and recognize difficult structures in high-dimensional data for application in agricultural endeavors. This is made possible by the fact that it is now possible to recognize high-dimensional data. After that, this information might be put to use.

In addition, we put a number of cutting-edge deep-learning frameworks through their paces by testing them with real-world data involving a wide variety of animals. Because of these testing, we were able to provide a more in-depth discussion of the difficulties connected with employing CNN for the purposes of both classification and detection. The primary objective of this research was to compare the performance of various classification and detection models in order to validate the effective application of DL, which is suitable for the sensors and equipment in PA. In order to do so, the research primary objective was to validate the effective application of Deep Learning. This was done so that the classification and detection architectures could be validated with faster speed and higher accuracy, both of which are essential for the production and management of agricultural crops.

2. Related works

In recent years, there has been a great deal of success with agricultural applications that are based on deep learning. These applications are also frequently referred to as smart agriculture. These programs make use of data received from a wide variety of sources in an effort to manage a number of agrarian tasks. There is a wide range of capabilities among AI-based intelligent systems in terms of their capacity to acquire and analyze data, as well as provide timely recommendations to farmers. One example of this capability is the ability to predict crop yields. In order to gather information, it is possible to set up nodes of the Internet of Things, which are also referred to as sensors. After that, any deep learning technique can be used to process this data, and actuators can be used to impose judgments on functional domains. In order to perform real-time monitoring and administration of agricultural operations, in addition to the AI system, other cutting-edge technologies are utilized. These technologies include remote sensing of geographical information, worldwide satellite placement, and automated computer control [10].

In addition, smart agriculture that is powered by AI is able to optimize the scheduling of resources such as fertilizer, insecticides, and water, which helps cut down on pollution as well as operational and production expenses while simultaneously increasing output. This allows for more food to be produced from the same amount of resources [11].

AI can help with the early identification and prevention of plant illnesses, it is beneficial to the environment to use less medication to stem the spread of plant diseases [12]-[14]. This is because AI can help with the early identification of plant illnesses.

A steady supply of agronomic inputs like as water, nutrients, and fertilizers must be provided to plants in order for them to preserve their highest possible levels of health, development, and production [15]. If they are absent, there is a chance that abnormally high levels of stress caused by both biotic and abiotic agents will be the end outcome. The only thing that can make the decision to use the optimal amount of a resource at the optimal moment is AI, because it takes into account both the current situation and projections for the future.

The AI is able to accomplish this by performing research on both the past and the present. This study investigated the current state of AI and deep learning in the agricultural sector as well as the prospects that are presented by these technologies. In addition, we researched the agricultural parameters that were monitored by the Internet of Things and included them into the deep learning models using this information.

3. Proposed Method

An approximation of the difference between the model projected value and the actual value can be calculated with the use of the Loss functions. This enables a more realistic representation of the disagreement to be made possible. This regularization term is a real-valued function that does not have a negative value, and it is commonly expressed by either L1 or L2. A cross-entropy loss function is implemented in our network so that computations can be carried out successfully. The formula for the loss function can be written out as follows:

$$J = \sum_{c=1}^{M} y_c \log\left(p_c\right) \qquad (1)$$

where

M - categories.

y - indicator variable

p - predicted probability

c - class.

The y-indicator variable is used to indicate the class, and the p-predicted probability variable is used to determine the likelihood of attaining a particular result. The prediction that was generated by your model, which is denoted by f(x), is compared to the actual value, which is denoted by Y, and the loss function is used to evaluate the degree to which the two values deviate from one another. It is applicable to values that are both nonnegative and real, and it can be represented as the notation L (Y, f). When the loss function has a smaller footprint, it is argued that the model has higher degrees of stability. The loss function is the basis for the construction of empirical risk functions and serves as their foundation.

3.1. Deep Learning classification - Convolutional Neural Network (CNN)

CNNs are a special type of deep learning architecture that are built using a significant number of convolutional layers, pooling layers, and fully connected layers. The CNN refers to this architecture. It is a neural network with multiple layers that is designed to mimic the visual cortex of animals and draws its inspiration from their behavior. Image processing and handwriting recognition are two of the most prominent applications for CNNs, however they are utilized for a broad variety of other tasks as well. CNNs have been put to use for a huge variety of tasks within the realm of computer vision.

Some of these activities include, but are not limited to, classification, object detection, picture segmentation, speech recognition, text and video processing, and medical image analysis. The convolutional, pooling, and fully connected layers make up the fundamental architecture of a CNN. These layers are in turn formed of the fully connected layer. Figure 1 presents an oversimplified representation of the numerous layers that are contained within a convolutional neural network (also known as a CNN). The function of each layer will be examined in greater detail:

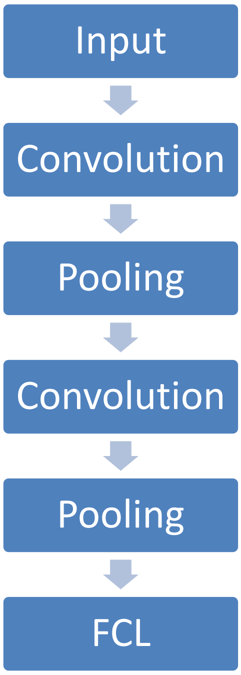

Figure 1. CNN architecture.

Convolutional Layer

When referring to a convolutional neural network, which is also referred to by its abbreviation CNN, the convolutional layer is the first and most important layer in the network. In order to generate an activation map for each image, the resulting pixel matrix is either rotated or multiplied in one of two ways. After then, this map is layered on top of the image. The fundamental benefit of using an activation map is that it is able to remember all of the distinguishing characteristics of an image while also reducing the amount of information that needs to be processed all at once. This will save a substantial amount of time.

By merging the data in a feature detector matrix, we are able to generate new picture variations at a variety of feature detector depths. In addition, backpropagation is utilized throughout the entirety of the complex model training process to ensure that each of its layers contains the least amount of error that is technically feasible. This is accomplished by ensuring that there is a positive feedback loop between each of the layers. The depth and padding of a fault set are going to be determined by the errors that make up the majority of a fault set. The process of obtaining features from images takes place within the convolutional layer of the neural network.

Pooling Layer

At this stage of the process, significant efforts are being made to reduce the number of dimensions in the activation map while retaining only the most essential details and as little of the extraordinary invariance as is humanly possible. These efforts are being made in conjunction with one another. It helps to solve the problem of overfitting by cutting down on the total amount of model features that may be learned.

Because of the pooling function, a CNN is able to reliably identify an object despite the numerous distinct angles and dimensions that are included in the image. This is the case even when the image contains a wide variety of perspectives. There are many various approaches to pooling resources, such as the maximum pooling method, the average pooling method, the stochastic pooling method, and the spatial pyramiding method, amongst others. The approach of maximal pooling is by far the one that is used the most.

Fully Connected Layer

The information needed for this layer of the neural network is obtained from the data stored in the preceding levels. Before being given over to the neurons, the matrix is typically flattened in the majority of cases. The information becomes muddled because there are multiple buried layers, each of which assigns a different weight to the output of each neuron. This causes the information to become jumbled. This location is responsible for carrying out all of the computations and logical reasoning pertaining to the data.

4. Results and Discussions

In this section, we use various CNN frameworks through their paces by testing them with real-world data involving a wide variety of animals. Because of these testing, we were able to provide a more in-depth discussion of the difficulties connected with employing CNN for the purposes of both classification and detection. As a direct outcome of this research, accurate scientific data for agricultural production and management was produced using CNN efficient application, which was shown to be suited for the sensors and equipment in Pennsylvania. Comparing the results of a number of different classification and detection models was the primary focus of this investigation because its primary purpose was to validate the classification and detection architectures with increased speed while maintaining a high level of accuracy.

Each model is trained asynchronously utilizing augmented data, and then four graphics processing units are used to make modifications to increase the number of trial iterations per unit of time (GPUs). In order to train our network for this particular experiment, we combined the training set and the verification set. We were able to recreate the settings of the initial model by using a batch size of 64 and an initial learning rate of 10^3; however, this resulted in a training process that is extremely unstable due to significant swings in the loss. It has been decided that there will be a total of 500 training epochs available to be used by everyone. We use the value of 0.00005 for the weight decay and the value of 0.9 for the momentum. These are the numbers that we use.

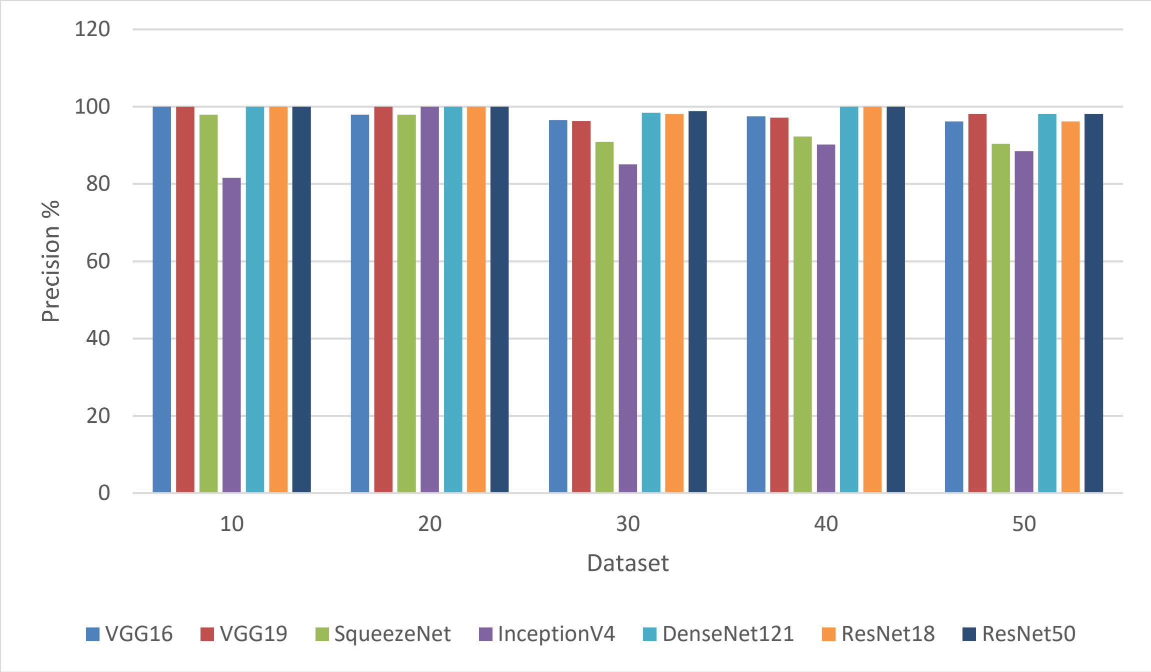

Figure 2: Precision

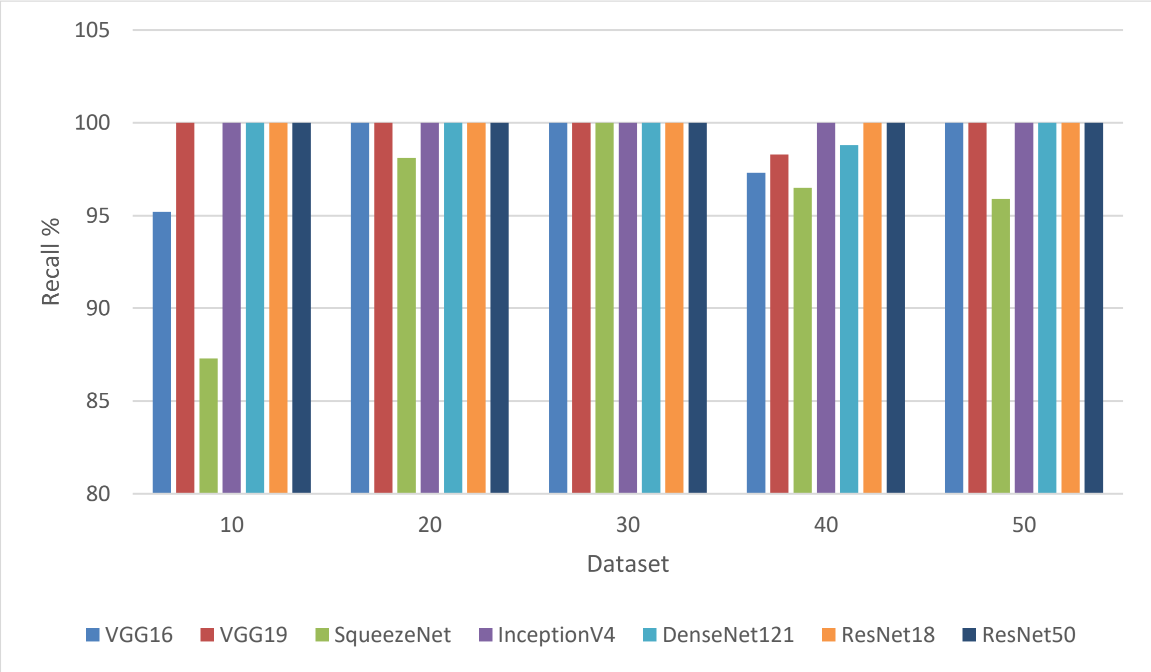

Figure 3: Recall

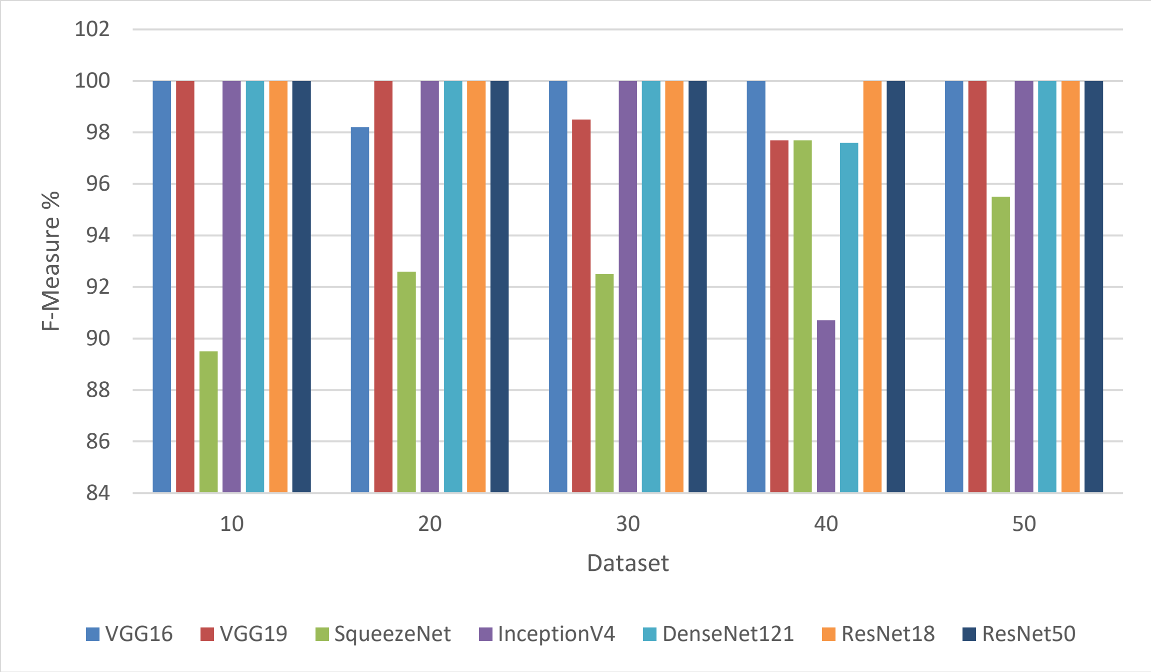

Figure 4: F-Measure

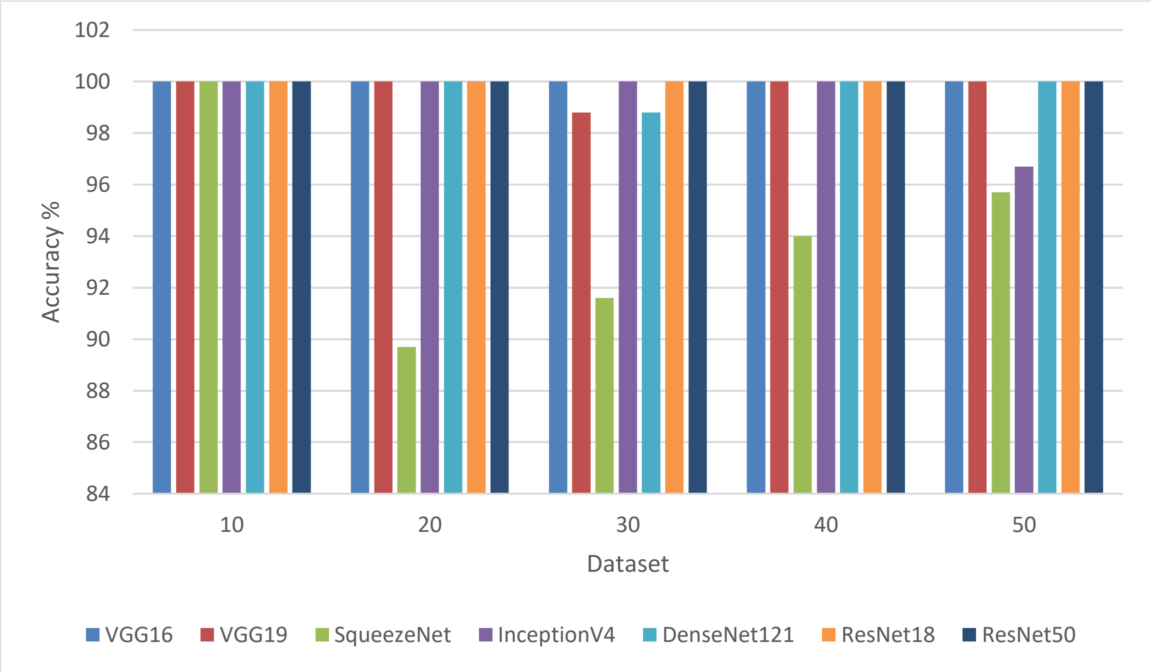

Figure 5: Accuracy

The results are shown in Figure 2- 5, where training images that are used for each and every class. This is what one may infer from the name. It would appear that the rates of success enjoyed by diverse crops are quite dissimilar to one another. When comparing the performance of ResNet networks, the ResNet50 has a higher capacity than the ResNet18, which contributes to the ResNet50 greater performance. Densenet 121 is a great option to consider in place of ResNet 18.

The low performance of VGG16 and VGG19 on plant village datasets, when compared to the architectures that were previously mentioned, is most likely due to over-fitting on categories with a limited number of training images. This is the case because VGG16 and VGG19 have fewer training images than the other architectures.

When the performance of fruits and vegetables was evaluated with and without the inclusion of Inception, it was found that, similar to the VGG architectures, the inclusion of Inception was negative due to the limited number of crop species. This was discovered when evaluating the performance of fruits and vegetables with and without the inclusion of Inception. SqueezeNet has a bad performance, despite the fact that it was created with embedded systems in mind during the design process.

5. Conclusions

The aim of the proposed DL is to bring the amount of variance that occurs between the actual findings and the estimated ones, as well as the number of false positives that are discovered in the final results, down to a more manageable level. This will be achieved by applying non-maximum suppression of the meta-architecture, which selects only candidates based on their initial annotated ground truth. This will be done in order to attain the aforementioned goal. In order to provide each model with as much support as is practically possible, we undertake evaluations utilizing images that feature either a single occurrence or numerous cases of the same species.

References

[1] Bu, F., & Wang, X. (2019). A smart agriculture IoT system based on deep reinforcement learning. Future Generation Computer Systems, 99, 500-507.

[2] Mekonnen, Y., Namuduri, S., Burton, L., Sarwat, A., & Bhansali, S. (2019). Machine learning techniques in wireless sensor network based precision agriculture. Journal of the Electrochemical Society, 167(3), 037522.

[3] Hannah, S., Deepa, A. J., Chooralil, V. S., BrillySangeetha, S., Arshath Raja, R., ... & Alene, A. (2022). Blockchain-based deep learning to process IoT data acquisition in cognitive data. BioMed Research International, 2022.

[4] Natarajan, Y., Srihari, K., Dhiman, G., Chandragandhi, S., Gheisari, M., Liu, Y., ... & Alharbi, H. F. (2022). An IoT and machine learning-based routing protocol for reconfigurable engineering application. IET Communications, 16(5), 464-475.

[5] Singh, D. K., & Sobti, R. (2021, October). Role of Internet of Things and Machine Learning in Precision Agriculture: A Short Review. In 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC) (pp. 750-754). IEEE.

[6] Natarajan, Y., Raja, R. A., Kousik, N. V., & Saravanan, M. (2021). A review of various reversible embedding mechanisms. International Journal of Intelligence and Sustainable Computing, 1(3), 233-266.

[7] Sen, A., Roy, R., & Dash, S. R. (2021). Smart farming using machine learning and IoT. Agricultural Informatics: Automation Using the IoT and Machine Learning, 13-34.

[8] Ullo, S. L., & Sinha, G. R. (2020). Advances in smart environment monitoring systems using IoT and sensors. Sensors, 20(11), 3113.

[9] Yang, J., Guo, X., Li, Y., Marinello, F., Ercisli, S., & Zhang, Z. (2022). A survey of few-shot learning in smart agriculture: developments, applications, and challenges. Plant Methods, 18(1), 1-12.

[10] Muniasamy, A. (2020, September). Machine learning for smart farming: a focus on desert agriculture. In 2020 International Conference on Computing and Information Technology (ICCIT-1441) (pp. 1-5). IEEE.

[11] Alrowais, F., Asiri, M. M., Alabdan, R., Marzouk, R., Hilal, A. M., & Gupta, D. (2022). Hybrid leader based optimization with deep learning driven weed detection on internet of things enabled smart agriculture environment. Computers and Electrical Engineering, 104, 108411.

[12] Zhu, N., Liu, X., Liu, Z., Hu, K., Wang, Y., Tan, J., ... & Guo, Y. (2018). Deep learning for smart agriculture: Concepts, tools, applications, and opportunities. International Journal of Agricultural and Biological Engineering, 11(4), 32-44.

[13] Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. Computers and electronics in agriculture, 151, 61-69.

[14] Bakthavatchalam, K., Karthik, B., Thiruvengadam, V., Muthal, S., Jose, D., Kotecha, K., & Varadarajan, V. (2022). IoT framework for measurement and precision agriculture: predicting the crop using machine learning algorithms. Technologies, 10(1), 13.

[15] Junior, F. M. R., Bianchi, R. A., Prati, R. C., Kolehmainen, K., Soininen, J. P., & Kamienski, C. A. (2022). Data reduction based on machine learning algorithms for fog computing in IoT smart agriculture. Biosystems Engineering, 223, 142-158.