



Weed Identification Using Convolution Neural Networks

B. Murali Krishna^{a,*}

^a Department of Computer Science and Engineering, MLR Institute of Technology, Hyderabad, India

* Corresponding Author: muralikrishna.b@mlrinstitutions.ac.in

Received: 05-08-2023, Revised: 12-11-2023, Accepted: 24-11-2023, Published: 13-12-2023

Abstract: Deep learning is the core component of the machine learning field which employs knowledge representation for learning. Learning can be supervised or unsupervised. More deep learning techniques can be used which will contain deep belief, deep neural, recurrent neural networks in it which will be used in many fields. The most commonly used applications in deep learning are vision, audio, video, language processing, social media, medical, gaming and there are so many other programs where this deep learning has already produced very perfect results when compared to other cases and in a very little number of cases with superior to experts i.e. humans. Techno Agriculture is the domain where the farmers will get benefited from these latest improvements in the expert system. One of main objectives is that in order to remove weeds or unwanted plants by reduction in the usage of herbicides and to decrease the pollution in both crop and water. One of the Neural Networks i.e. CNN uses a flexible layer with the function of a ReLU to extract image elements and then uses a high-resolution and fully integrated RELU layer to separate weeds from the plant. The image which was processed previously is used on the convolution neural network which in return gives an image from the Region of Interest (ROI) from where it will extract the image and remove the certain aspects of the image in the training phase, after the training a splitting operation will be performed and the weeds are therefore classified by using the deep learning technique. In this scenario we trained 100 images in order to increase the accuracy of the model.

Keywords: Weeds and Crops Classification, Shape Features, Convolution Neural Network, Contour Property, VGG 19, Machine Learning

1. Introduction

Agriculture or Farming is the occupation for many people in India and it is the primary source of income for the people who live in India. In India almost 58% of the entire population depend on agriculture for their livelihood. The suggestion is to identify weeds planted between plants using a deep learning method and weed removal. An image of a vegetable garden is provided as an example of input training. An in-depth learning model has been developed using

the CNN to detect weeds with good accuracy. So, the model can identify weeds in a short period of time [1]. In-depth reading is used to analyze relevant features from agricultural images. The use of herbicides will have a major impact on both the soil and the crop. So, it is better to identify the weeds among the crop by using a computer or any device so that accordingly they can be removed to increase the crop yield. In this method the images are taken or captured by the camera and after capturing image preprocessing is performed on the captured image and the features from the image are extracted. According to the features discovered the network will be trained for classification.

2. Literature Survey

Ahmed *et al* [2], developed our study is to assess the effectiveness of using Support Vector Machines (SVM) as the classification model in an automated weed management system by determining the classification rate achieved. They have conducted tests to evaluate the effectiveness of different combinations of features in classifying crops and weeds in photos. A total of fourteen features were investigated to identify the ideal combination that yields the highest classification rate. The analysis of the results indicates that the Support Vector Machine (SVM) achieves an accuracy of over 97% over a set of 224 test photos. Crucially, there is no misidentification of crops as weeds or vice versa.

Siddiqi *et al* [3], they suggested method was evaluated using a database consisting of 1200 samples, which is significantly bigger than the database sizes examined in prior studies (200-400 samples). The crop/weed classification results produced from several wavelet transforms at different compression levels were compared using confusion matrices. Additionally, this approach was compared to existing techniques that utilise statistical and morphological methodologies. The simplest wavelet family achieved an overall classification accuracy of 98.1%. The results demonstrate a 14% enhancement in performance when compared to current methodologies.

Recent studies have demonstrated that Deep Residual Networks greatly enhance the performance of neural networks trained on ImageNet. These networks have achieved superior results in the picture classification test, surpassing all previous methods by a wide margin. Nevertheless, the significance of these remarkable figures and their consequences for future investigations remain incompletely comprehended at present. This review aims to provide a comprehensive explanation of Deep Residual Networks, including their exceptional performance, and the tremendous progress they represent compared to other techniques when successfully implemented in practice. In addition, we address unresolved issues with residual learning and explore potential uses of Deep Residual Networks that extend beyond ImageNet. Lastly, we will address certain unresolved matters that must be dealt with prior to the application of deep residual learning on more intricate problems [4 - 8].

Detecting crop viruses in the agricultural sector is extremely challenging. Inaccurate detection can lead to a decline in crop output and a significant loss in market value for the product. This highlights the necessity for novel tools that aid in the identification of crop illnesses and their development. The primary objective of this proposed model is to concentrate on the agricultural and agro-based industry by detecting and predicting plant illnesses. Early detection and identification of agricultural diseases aid farmers in implementing required safeguards and procedures, hence enhancing crop output [9- 14].

The study presented innovative findings for five distinct screening and clinical grading systems used in the classification of diabetic retinopathy and macular oedema. These results include cutting-edge accuracy in classifying images based on the clinical five-grade diabetic retinopathy scale, as well as the first-ever achievement in precisely categorizing images corresponding to the four-grade diabetic macular oedema scale. These findings indicate that implementing a deep learning system could enhance the cost-effectiveness of screening and diagnosis, while achieving performance levels greater than what is currently advised. Additionally, this method could be utilized in clinical tests that necessitate more precise grading [15- 17].

3. Proposed System

Agriculture is now a very important sector that everyone should pay attention to help farmers. The population in our country is growing rapidly in recent years due to which the demand for food is growing so directly or indirectly the farm products demand is also growing day by day. Therefore, farm yields play an important role. New methods are emerging now in the day to keep the crop high by considering the environmental impact. One of the most important steps in increasing yields is weed control as it is directly related to crop yields. So here we are considering weed identification in the farm field using an in-depth study method. Here we are using one of the deep learning techniques i.e. we are using a convolutional neural network to identify weeds.

3.1 CNN

Convolutional neural network (CNN) falls under the artificial neural network (ANN) which performs image detection, image classification and processing of the image that is specially developed to process plant or weed images i.e. input images. The neural networks with multiple layers acts like a system of both hardware and software patterned following the process of neurons in our brain. Various old methods of artificial networks are not efficient for handling images and they impose network input images which should be reduced and its resolution decreases. CNN proposes a multi-layer perceptron-like model designed for practical and low-cost computing needs. There are three different types of layers on CNN that contain input layer, output layer and many hidden layers, where the data from the image is scanned using image pixels, these three different layers include several layers of convolution to extract image elements and then

using layers to combine to lower that image. In addition, it also includes fully connected layers and an additional layer called as normalization layers at the end of the CNN.

3.2 Neural Networks

The convolution layer is one of the central components of the CNN architecture that plays an important role in extracting features from the input image. The sharing of link weights by all neurons in a specific feature map extracted from the image is done in this part. Neurons in a layer are only connected to a subset of the given input image which helps to optimize the number of hyper parameters in the architecture and helps to improve the computation efficiency of the model. The farmers of our country should be made aware of the different types of weeds and should give them the knowledge of the condition of weeds in their fields. This can help them to reduce the use of herbicide in large quantities in agriculture, so that they can spray it as little as possible which in turn reduces the consumption of herbicide. The development of an automated system for an effective and precise weed control is a set of computer vision and its associated areas. The proposed model is able to group weed varieties on the basis of their similarity and also to understand the amount of leaves with a satisfactory level of accuracy. In order to identify types of weed species and to develop a robust and accurate system with plant leaves, the captured images are required to wrap natural variation in terms of ecological conditions and stages of plant developmental progress. These conditions include the setting of sunlight, the nature of the soil and the condition of the plants. A central problem with automatic leaf identification and counting is that the leaves of weeds are usually stacked on top of each other. Completely automated systems developed to measure plant count with the computer vision techniques which are limited to binary range images [8, 9, 18, 19].

3.3 Modules

- a. **Dataset:** weeds and plants dataset are collected from Kaggle and various types of weeds and plants are used as features and weeds plants are used as labels.
- b. **Preprocessing:** before training data each image is converted to 224*224 size and re-scale image.
- c. **Split data:** data set is divided into testing and validation dataset which is used for train and test.
- d. **Initialize Model:** In this stage VGG 19 model is initialized with required parameters and trained features and labels are fit to algorithm and model is saved to system.
- e. **Prediction:** User uploads weeds and plants as images as input to web application and check with model to predict result.

3.4 Architecture

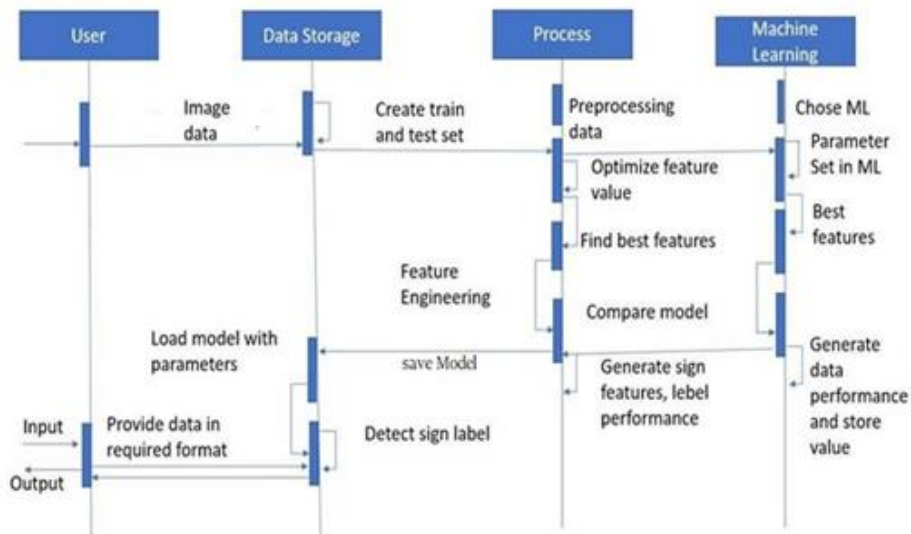


Figure 1. Working of VGG19

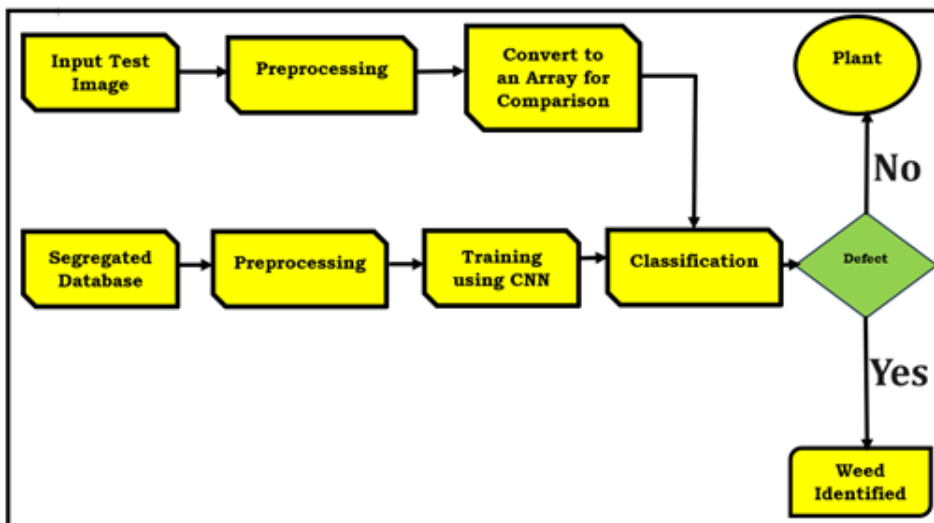


Figure 2. Working of CNN

In Figure 1 and Figure 2 consists of the working of VGG 19 under the model of CNN. The above model consists of 2 ways in the first way the input test image is taken and it is sent to pre processing and further the image is converted into an array for comparison with the pretrained model. Next the segregated database consists of the test images and it is sent in the similar way to the preprocessing and the image will be trained using CNN Algorithm both the test image and the array are sent to classification where the machine learning algorithm detects

the test image as plant or a weed. Case1: If the output is given as plant the machine will detect and compare the test image with predefined image and gives an output as it is a healthy plant. Case 2: If the output is given as weed then the machine will detect and compare the test image with predefined image and gives an output stating that it is a weed.

Pooling is a process which consists of pooling layers which are actually help for down sampling the feature maps by adding up the features into a feature map. There are 2 common types of merging methods which are intermediate mergers (which summarizes the intermediate presence of the feature) map shown in Figure 3.

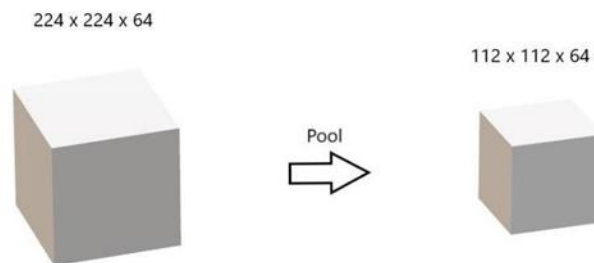


Figure 3. System pooling

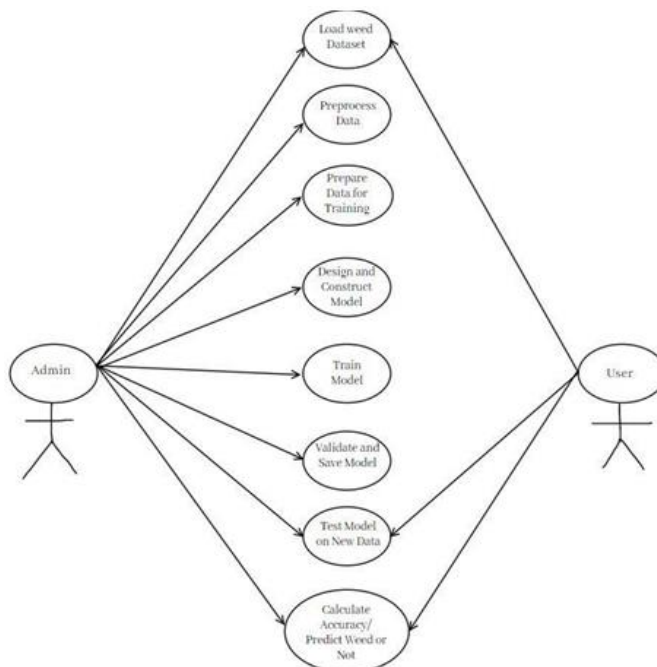


Figure 4. Working of Model

Pooling is mandatory step in systems; based on convolution network will reduce the dimensionalities of the feature maps. It combines a set of values into a smaller number of values. It transforms the joint feature representation into valuable information by removing the

unwanted information and keeping the useful information which helps the system. The polling operators also supervisor special feature while reducing the complexity of the calculation between the upper layers by removing the contact between the convolutional layers. This layer uses a low-sample approach - on feature maps from previous layers and that will produce a new featured editable map.

The Process of evaluating a particular system and its individual components to find or verify that it would satisfy the expected output or requirements is known as Testing. Testing is actually a manual or an automated process of checking the system for any errors or gaps (i.e. missing any requirements) to the actual needed requirements.

3.5 Evaluation

Plants and weeds are classified on the basis of their features only. In the work, their area, perimeter and eccentricity values are calculated exactly making them the right training model. The values are differed for plants and weeds. Based on this value the classification is done. The user information is shown in Figure 5, 6 and 7 respectively.

3.6 Sample Dataset

	id	name	image	username
<input type="checkbox"/>	7		9.jpg	chotu
<input type="checkbox"/>	8		agri_0_60.jpeg	john wick
<input type="checkbox"/>	9		agri_0_395.jpeg	john wick
<input type="checkbox"/>	10		agri_0_2469.jpeg	john wick
<input type="checkbox"/>	11		agri_0_131.jpeg	bahu
<input type="checkbox"/>	12		agri_0_657.jpeg	bahu

Figure 5. User Information



Figure 6. Weed dataset



Figure 7. Plant dataset

3.7 Result

The result of the above data set classifies the image into particular data set, whether it belongs to plant data set or weed data set basing upon its training the machine will recognize into which category is it. Case1: - so, in that case one if the image is recognized as a weed the machine will state that it's a weed in the category and description. Case 2: - if the image is recognized as a plant, then the machine will automatically recognize and show it is a plant. With this approximation of the images the user will get a better knowledge upon what type of autotroph it is as shown in Figure 8 and Figure 9.

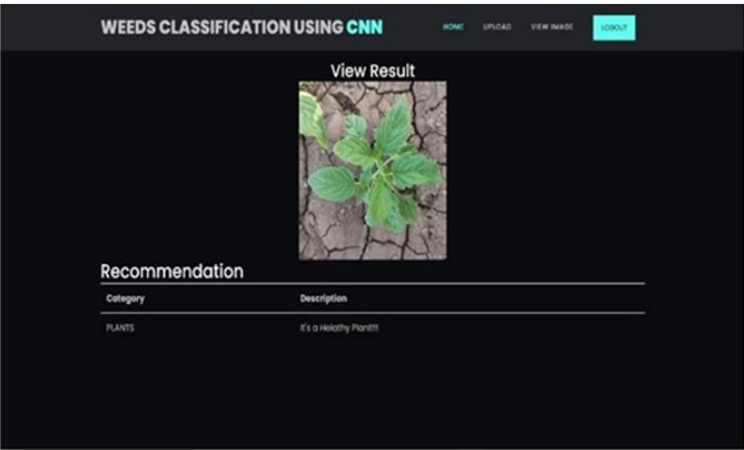


Figure 8. Resulting it's a plant

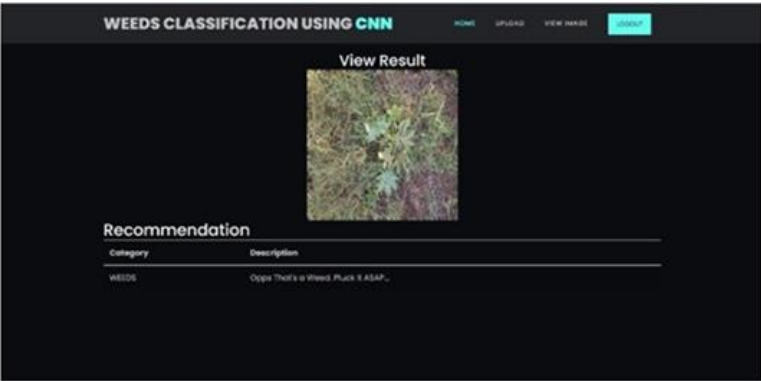


Figure 9. Resulting it's a Seeds

3.8 Precision

The training and precision are the most important part of a project the president of our project consists of around 75% true to its nature and it detects any type of weed or plant present

in the new datasets which can be trained with the machine and they can be also kept as a reference for the future works. The detailed analysis is clearly shown in Figure 10 and Figure 11.

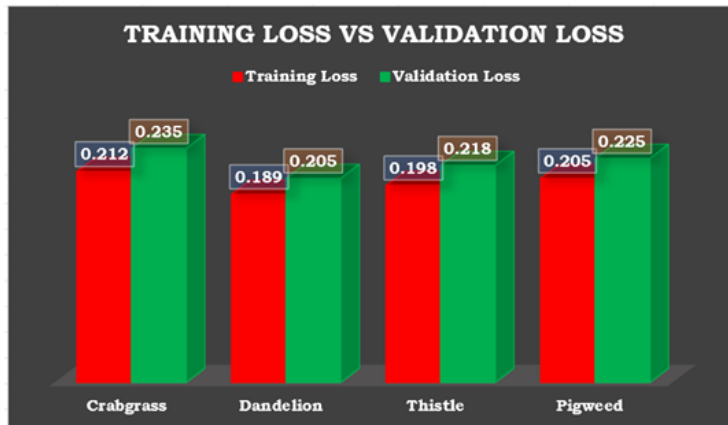


Figure 10. The Validation Loss Analysis of the Proposed Method

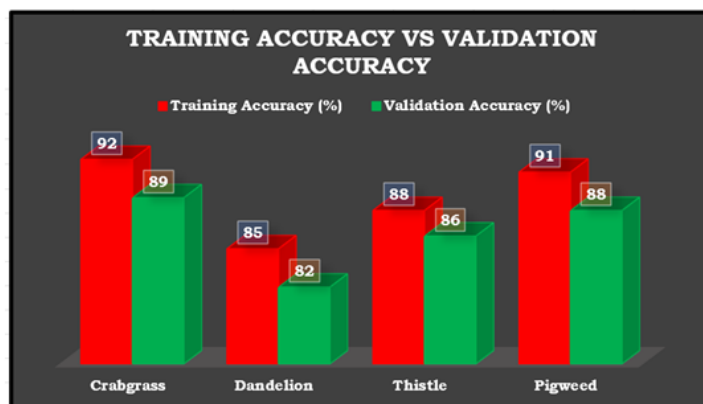


Figure 11. The Validation Accuracy Analysis of the Proposed Method

4. Conclusion

Feature extraction method is a concept used for reducing the amount of computation and storage resources required to state and process large datasets. In this proposed work, CNN classification is used to extract the prominent features and the specific significant features which are used for effectively training the model. The proposed model gives an accuracy of 62%. In the future, action marks shall be taken to improve the accuracy and to evaluate the model with other significant features or parameters. The methodology proposed in this article would be extended further to other plants and weeds with higher boundaries in the field that contains various categories of autotrophs. In future, RNN classification shall be used to extract the

important features and extract the most significant features that are used for effective training of the model.

References

- [1] P. Chinnasamy, K.B. Sathya, B.J. Jebamani, A. Nithyasri, S. Fowjiya, (2023) Deep Learning: Algorithms, Techniques, and Applications – A Systematic Survey, *Deep Learning Research Applications for Natural Language Processing*, 17. <https://doi.org/10.4018/978-1-6684-6001-6.ch001>
- [2] F. Ahmed, H.A. Al-Mamun, A.S.M.H. Bari, E. Hossain, P. Kwan, Classification of crops and weeds from digital images: A support vector machine approach, *Crop Protect*, 40, (2012) 98–104. <https://doi.org/10.1016/j.cropro.2012.04.024>
- [3] M.H. Siddiqi, S.W. Lee, A.M. Khan, Weed Image Classification using Wavelet Transform, Stepwise Linear Discriminant Analysis, and Support Vector Machines for an Automatic Spray Control System, *Journal of Information Science & Engineering*, 30(4), (2014) 1253-1270.
- [4] Garford, (2018) Robocrop Spot Sprayer, Available at: <https://garford.com/wp-content/uploads/2018/08/spot-sprayer.pdf>
- [5] A. Bakhshipour, A. Jafari, Evaluation of support vector machine and artificial neural networks in weed detection using shape features, *Computers and Electronics in Agriculture*, 145, (2018) 153-160. <https://doi.org/10.1016/j.compag.2017.12.032>
- [6] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, Z. Wojna, Rethinking the Inception Architecture for Computer Vision, in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, USA. <https://doi.org/10.1109/CVPR.2016.308>
- [7] K. He, X. Zhang, S. Ren, J. Sun, (2016) Deep residual learning for image recognition, *Proceedings of the IEEE conference on computer vision and pattern recognition*, USA. <https://doi.org/10.1109/CVPR.2016.90>
- [8] C. Henschel, T.P. Wiradarma, H. Sack, (2016) Fine tuning cnns with scarce training data—adapting imagenet to art epoch classification, *IEEE International Conference on Image Processing (ICIP)*, USA. <https://doi.org/10.1109/ICIP.2016.7533049>
- [9] E. Anupriya, M. Thaile, P. Chinnasamy, P.M. Yasaswini, (2023) Image Based Plant Disease Detection Model Using Convolution Neural Network, *International Conference on Computer Communication and Informatics (ICCCI)*, India. <https://doi.org/10.1109/ICCCI56745.2023.10128618>
- [10] V. Praveena, P. Chinnasamy, P. Muneeswari, R. Ananthakumar, Detection and Categorization of Plant Leaf Diseases using Neural Networks, *European Journal of Molecular & Clinical Medicine*, 7(4), (2020) 2438-2445.
- [11] N. Iqbal, S. Manalil, B.S. Chauhan, S.W. Adkins, Investigation of alternate herbicides for effective weed management in glyphosate-tolerant cotton, *Archives of Agronomy and Soil Science*, 65(13), (2019)1885–1899. <https://doi.org/10.1080/03650340.2019.1579904>

- [12] Weed, Precision spraying - weed sprayer. (2021). Retrieved January 25, 2021, from <https://www.weed-it.com/>
- [13] Garford, Robocrop spot sprayer: Weed removal. (2018). Retrieved January 25, 2021, from <https://garford.com/products/robocrop-spot-sprayer/>
- [14] C.F. Sabottke, B.M. Spieler, The effect of image resolution on deep learning in radiography, *Radiology: Artificial Intelligence*, 2(1), (2020) e190015. <https://doi.org/10.1148/rvai.2019190015>
- [15] J. Sahlsten, J. Jaskari, J. Kivinen, L. Turunen, E. Jaanio, K. Hietala, K. Kaski, Deep learning fundus image analysis for diabetic retinopathy and macular edema grading, *Scientific reports*, 9(1), (2019) 10750. <https://doi.org/10.1038/s41598-019-47181-w>
- [16] K. Simonyan, A. Zisserman, (2014) Very deep convolutional networks for large-scale image recognition, *arXiv*.
- [17] D. Slaughter, D. Giles, D. Downey, Autonomous robotic weed control systems: A review, *Computers and electronics in Agriculture*, 61(1), (2008) 63-78. <https://doi.org/10.1016/j.compag.2007.05.008>
- [18] P. Chinnnasamy, K.S. Sathya, R.K. Ayyasamy, V. Praveena, T.S. Arulananth, Defect Exposure in Vegetables and Fruits Using Machine Learning Algorithms, *CRC Press*. <https://doi.org/10.4324/9781003388982-47>
- [19] K.S. Prasad, K. Shekar, P. Chinnnasamy, A. Kiran, K.A. Mohamed Junaid, B. Rachana, (2023) Plant Disease Prediction Using Convolutional Neural Networks, *International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE)*, India. <https://doi.org/10.1109/RMKMATE59243.2023.10369533>

Funding

No funding was received for conducting this study.

Conflict of interest

The Author have no conflicts of interest to declare that they are relevant to the content of this article.

About The License

© The Author 2023. The text of this article is open access and licensed under a Creative Commons Attribution 4.0 International License.