Hybrid Algorithm of Convolutional Neural Networks and Vector Support Machines in Classification

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Abstract. Looking for the improvement of the classification, we propose a hybrid algorithm to identify the corn plant and the weed. With the aim of improving the fertilization and herbicide application processes. An efficient process can avoid wasted fertilizers and decrease subsoil contamination. The purpose is to identify the corn plant to specify the fertilizer application in an automated and precise way. Whereas, the identification of the weed allows to apply herbicides directly. In this work we propose a hybrid method with Convolutional Neural Networks (CNN) to extract characteristics from images and Vector Support Machines (SVM) for classification. We obtained effectiveness results, a percentage of 98%, being higher than those compared to the state of the art.

Keywords: Classification · Convolutional neural network · Support vector machine · Hybrid algorithm

1 Introduction

According to the national agricultural survey in Mexico (NAS, 2019), corn is the second crop in the country in terms of annual production, surpassed only by sugar cane, but above crops such as wheat, sorghum, tomato, Chile and beans [1]. Of the 64 breeds reported in Mexico, 59 can be considered native. Mexico is the cradle of corn. Also, it is the origin of an enormous diversity of varieties. The corn has been the sustenance of their peoples. The population uses corn in countless ways. Finally, corn is the source of cultural and social wealth for Mexicans [2].

Chemical fertilizers unquestionably have effects on the environment. Fertilizers generate a high risk of environmental damage. Fertilizers can contaminate subsoil groundwater in the area of application. A fertilizer is a substance that is used to provide nutrients to the soil. The objective of fertilizers is to increase the concentration of nutrients to favor and promote plant growth [3].

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We must currently rely on new technologies, for example: sensors, big data or deep learning. We must move towards smart agriculture. Smart farming technology can help increase crop yields. On the other hand, it could also support the control of weeds with high precision in different stages of growth [4].

Weeds are considered one of the main threats in agricultural production. Weeds can cause a significant loss of yield at harvest. Weeds compete for nutrients, sunlight, space, and water. Weeds also cause loss of product quality. Finally, weeds harbor insects or diseases [5].

Therefore, the recognition of weeds automatically with great precision is urgent. A weed identification can help in the application of herbicides and fertilizers in specific spaces.

Deep learning is a sub-area of machine learning. Deep learning is a new way of learning representations from data, images, sounds, or videos. Deep learning uses a series of successive layers of increasingly meaningful representations. The number of layers that contribute to a model of the data is called the depth of the model. Layered representations are almost always learned using models called neural networks. The architecture consists of structured in layers literally stacked one on top of the other. Deep learning often requires tens or even hundreds of successive layers of representations. The model learns automatically from the training data [6].

By definition, a deep architecture is a multi-stage hierarchical structure. Each stage is made up of a neural network with at least three layers. The neural network is trained through the Backpropagation algorithm. Neural network training with multiple layers in between fosters the emergence of several clustered algorithms in an area of study known as deep learning. The algorithms use two or more layers. Algorithms have the main objective of learning, not only to distinguish between classes based on artificial descriptors, but also to be able to learn their own descriptors based on raw data. For images, learning is based on pixel values [7].

Convolutional Neural Networks (CNN) are architectures inspired by biological neurons. CNNs are capable of being trained and learning representations. CNNs can learn without variation in terms of scale, translation, rotation, and similar transformations [8]. CNNs are used with two-dimensional data, which makes them a good choice for the image recognition process [9].

Support Vector Machines (SVM) are used to classify and recognize patterns in various types of data. The SVM are also used in a wide range of applications, such as facial recognition, clinical diagnostics, industrial process monitoring, and image processing and analysis [10].

Image recognition (IR) remains an open research issue. Image recognition requires the exploration of new techniques and methodologies. The IR requires further improvement in: performance in terms of recognition accuracy, execution time, and computational complexity. Therefore, in this work we propose a hybrid CNN-SVM method for the recognition of images of corn and weeds. The objective of this work is to extract the characteristics of the images of corn and weeds using a CNN, then the SVM classifier is applied to the learned characteristics for their classification.

We propose a method that classifies images of corn and weeds automatically. We obtained an excellent percentage of precision compared to those found in the state of the art. In the literature, hybrid methods are being proposed to solve problems involving feature extraction and image classification. Some research works that are mentioned present percentages of precision in the identification of images with a percentage greater than 90% of precision.

2 State of the Art

A number of studies that include the use of deep learning have reported state-of-the-art achievements in a considerable number of tasks. Some achievements are: image classification, natural language processing, speech recognition, symbol and text classification, as well as the classification of plants, weeds and diseases in various crops.

Silva et al. [11] present a tool for the recognition of cattle brands using CNN and SVM. In the experiments, the authors used 12 cattle brands and a set of 540 images and the precision obtained in the experiment reached 93.28%. The same author [12] Silva et al. in another work he carried out two experiments reaching indices of 93.11% and 95.34%, respectively, in the recognition of cattle brands.

Niu et al. [13], present an algorithm that uses a CNN and SVM to solve the problem of text recognition, achieving a recognition rate of 94.40%. Abien et al. [14] proposes a hybrid model capable of recognizing symbols from the MNIST database with an accuracy of 91.86%.

Hend et al. [15] present excellent precisions like the one proposed for recognition of human activity using a pre-trained CNN with 1.2 million high resolution images of the ILSVRC2015 classification training subset of the ImageNet dataset. The results generated were 99.92% Accuracy. In this case, it is necessary to mention that they used a pre-trained network with more than 14 million images. The number of images may be the reason that your tests have returned the excellent percentage.

The use of deep learning is also described in the research carried out by Constante et al. [16], who used a three-layer neural network with input through backpropagation; used this method to classify strawberries and obtained recognition results of 92.5%.

Garcia et al. [17] classified 20 kinds of common fruits in Mexico. The best classified fruits in the experiments were: pineapple and lemon with an effectiveness percentage of 97.68%.

Cervantes [18] mentions that current identification methods involve advanced algorithms to measure the morphological and texture characteristics of the objects contained in the image. These features provide a lot of information for classification.

Yang [19] addresses the problem of distinguishing corn plants from weeds, using an artificial neural network (ANN) using the Backpropagation algorithm. The results obtained were a detection percentage in corn of 100% and in weeds of 80%, that is, 90% on average.

Barufaldi [20] exposes the problem of weed recognition on a cultivated field. He applied Deep Learning techniques. The proposed vision system is based on a CNN and uses an SVM. The results for weed identification was 91%.

Haug et al. [21] proposed an artificial vision approach to discriminate crops and weeds in carrot crops, achieving a precision value of 93.8%. His Hnin et al. [22] developed a method to discriminate between crops and weeds with a classification percentage of 66.7%.

García-Amaro et al. [23] used traditional image processing techniques to detect diseases and pests in the tomato plant. They used the SVM algorithm achieving the best result of 93.86% accuracy.

Lanlan Wu [24] proposed a tool for classifying and identifying weeds in maize fields at the early stage of growth, using an SVM. The results showed that the SVM classifiers were able to successfully identify weeds with 100% accuracy.

In some cases, identification of crops and weeds was made possible by the SVM technique. The objective was to identify three categories: crops, soils and weeds. The identification of crops and weeds undoubtedly allows for various future applications. The proposal reached 94.3% accuracy in identifying the three categories. The solution could be used in vehicles, autonomous tractors [25] and robots.

In the literature we find that there are methods similar to ours, such as that of Campos et al. [25] that classifies crops, soil and weeds with a precision percentage of 94.3%; [26]. Jiang et al. classified corn and weeds with an effectiveness of 96.51%. [27] Yang Li et al. classified corn, apples and grapes with a precision of 94%.

Computer vision is the key technology to correctly identify corn plants and can differentiate them from weeds. The above could improve the fertilization and fumigation processes in an automated and precise way [3].

3 Methodology

LeCun et al. [28] developed the CNN, which is a hierarchical neural network and has an enormous capacity for representation that learns the significant characteristics at each layer of the visual hierarchy. Features are automatically extracted from the input image. Feature extraction has the advantage of being invariant to displacement and shape distortions of the input textural images. Recently, some deep learning architectures are switching from the engineering feature extraction phase to machine processing. With the new method, deep neural networks go directly into the raw data without human intervention to extract deep features [14].

Obtaining the Images: An image dataset of corn and weed plants was not found on the Internet. The image dataset needs specific characteristics according to the experiment of each investigation. In this work, we have used a high resolution image dataset obtained by ourselves. The images were obtained from a corn crop in the municipality of Francisco I. Madero in the state of Hidalgo, Mexico.

Dataset Organization: The problem of classification in unbalanced data sets currently represents a significant challenge for the artificial intelligence, data mining and machine learning scientific communities. There are several factors that make a problem of this type complicated, for example, imbalance between classes, imbalance within classes and anomalous instances [34]. External methods perform pre-processing on unbalanced data sets to meet one or more of the following objectives: balance the data set, remove instances considered noise, remove overlap between classes, or search for prototypes that represent the set of data in a way that is easy to process by classification or grouping methods.

This is the reason why the Dataset used is our own and the images were collected to maintain a balance of data that allows to obtain better results in the classification.

The images used in this investigation were 1000, of which 500 are of corn and 500 of weeds. We create two groups of images. The first group contains 80% for training. Whereas, the second group contains 20% for validation. The set of images were used without prior pre-processing such as normalization or dimensionality reduction, see Table 1.

Table 1. Dataset image features

Class	Quantity	Width	Height	Format
Corn	500	768	1024	JPG
Weed	500	768	1024	JPG

Method: The proposed method includes: the storage of the image dataset, the processing of the algorithm and the visualization of the results. We use a MacBook Pro personal computer with a 2.6 GHz Intel Core i5 processor with 8 GB of RAM. The code was written in Python version 3.5.

The dataset was used, without prior pre-processing such as normalization or dimensionality reduction. There are 1000 high resolution images, where 80% were for training and 20% for validation.

CNNs have the advantage of reducing the number of parameters and connections used in the artificial neural model to facilitate their training phase. The adopted method is a neural network with three convolutional layers.

In this section, we present the architecture of our method based on CNN and SVM. CNN is considered a deep learning algorithm on which the Dropout technique has been applied during training. Our proposed method was adapted by modifying the CNN trainable classifier by a linear SVM classifier. Our goal was to blend the respective capabilities of CNN and SVM. Our algorithms allowed us to obtain a new image recognition process for corn and weeds. We seek successful results inspired by the combination of the two powerful algorithms.

The initial CNN layers extract global features from the original images. However, the last fully connected layers draw out more distinctive features. These layers can extract features, which are increasingly stable to local transformations of the input image. For the training procedure, the SVM takes the results of the units as a vector of characteristics. The training phase continues until a good training is achieved. For the test process, the SVM classifier performs the classification on the test suite using these characteristics automatically. In summary, in the hybrid model that we propose, the CNN functions as a feature extractor and the SVM as a binary classifier.

The architecture of the proposed CNN-SVM hybrid model is described in the Fig. 1:

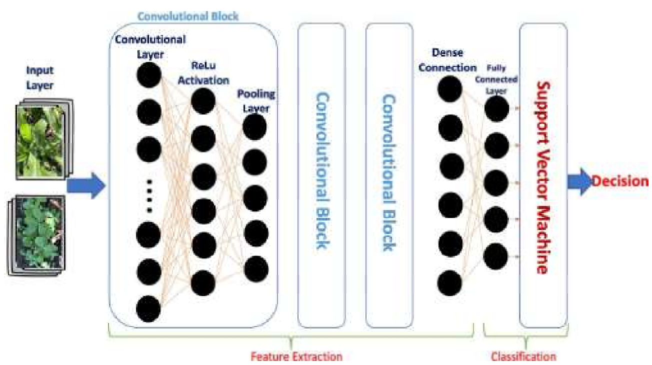

Fig. 1. CNN + SVM hybrid model architecture

The model consists of a 3-layer CNN architecture and an SVM classifier. In the CNN input layer, resize the original image and take a 150×150 matrix of corn or weeds, that is, an image of 150 pixels by 150 pixels of our Data set. In the convolutional layers, a 3×3 convolutional filtering and a stride of size 1 were used. The CNN was trained after executing 50 epochs and until the training process converged. The last layer of the CNN was replaced by an SVM linear classifier. The characteristics of the input image obtained in the third layer were treated as input to the SVM classifier. The SVM classifier is initially trained with these new features automatically generated from the training images. Finally, the SVM classifier is used to recognize the corn or weed images used for the test.

In Fig. 2 we can see the general architecture of a CNN, this to get an idea of the difference between the characteristics that a normal CNN has and the CNN combined with the SVM shown in Fig. 1 and which is our proposed method.

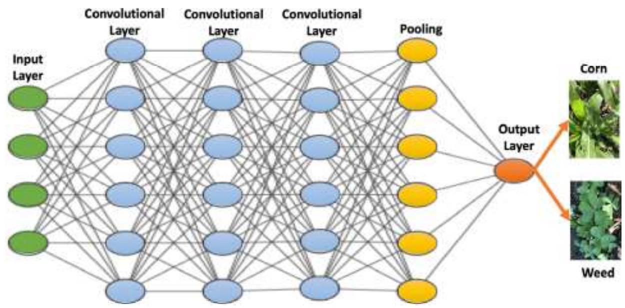

Fig. 2. CNN general architecture.

Common practice in most recent CNN developments focuses on implementing larger and deeper models to achieve better performance. The disadvantage arises when as the model gets bigger and deeper, the parameters of the network increase dramatically; as a result, the model becomes more complex to train and more computationally expensive. Therefore, it is very important to design an architecture that provides better performance using a reasonably fewer number of parameters in the network [35], such as the one proposed in Fig. 1.

Algorithms: The deep learning-based model is considered as one of the best rankings in pattern recognition tasks to improve analytical results [29].

On the other hand, SVMs are considered one of the most robust algorithms in machine learning created by Vapnik [30]. SVMs have become a well-known and exploited approach in many areas such as pattern recognition, classification, and image processing. The SVM was developed for binary classification and its objective is to find the optimal hyperplane.

The difference between a CNN and a multilayer perceptron network is the use of convolutional layers, clustering, and non-linearities like tanh, sigmoid, and ReLU. That is, the multilayer perceptron is an artificial neural network formed by several layers, in such a way that it has the ability to solve problems that are not linearly separable, which is the main limitation of the simple perceptron. The multilayer perceptron can be locally or fully connected. Whereas, CNN is a type of supervised learning neural network that processes its layers to identify different characteristics in the inputs that make it able to identify objects. Specialized hidden layers with a hierarchy can detect lines and curves in the first layers and are specialized until they reach deeper layers that recognize complex shapes such as a face or the silhouette of a plant.

Convolutional neural networks are used to extract features due to their strong ability to extract features [31]. The original images were uploaded to CNN, then the convolution operation of each layer was performed to acquire the characteristics of the image. The lower layer contains more spatial details, while the upper layer has more semantic information [31]. In order to obtain robust features from CNN, the output of the final grouping layer is used as a feature map of the image. The characteristic map goes directly to the SVM classifier to make the decision and thus know if an image corresponds to a corn plant or weed.

4 Results and Discussion

The results obtained during the tests performed are shown using the following abbreviations in Table 2: Acc = Accuracy; S = Sensitivity; E = Specificity; P = Precision; F-m = F-measure and MCC = Mattew's Correlation Coefficient, which are the performance measures generated in the results.

Table 2. CNN and SVM results

Algorithm	S	E	P	F-m	MCC
CNN + SVM	**98**	94	**98**	96.96	94

In Table 3 you can see the results compared with the results obtained with different methods found in the state of the art. The mentioned percentage corresponds to the Accuracy metric.

Table 3. Comparison of results obtained versus state of the art

Name	Images	CNN	SVM	CNN + SVM
Silva et al. 2019	Cattle brands	–	–	93.28
Silva et al. 2020	Cattle brands	–	–	95.34
Niu et al. 2011	Texts	–	–	94.4
Abien et al. 2019	MNIST symbols	–	–	91.86
Campos et al. 2017	Crop, soil and weeds	–	–	94.3
Jiang H. et al. 2020	Corn and weeds	–	–	97.51
Yeshwanth Sai et al. 2020	Dogs	–	–	93.57
Miao Ma et al. 2016	Hand gestures	–	–	96.1
Yang Li et al. 2020	Corn, apple and grape	–	–	94
Zhicheng Wang et al. 2017	Fire detection	95.79	–	–
Dechant et al. 2017	Blight on the corn husk	96.7	–	–
Sibiya 2019	Corn diseases	87 – **99**	–	–
Xihai Shang et al. 2017	Corn diseases	**98.8** y **98.9**	–	–
Sumita Mishra et al. 2020	Corn diseases	88.46	–	–
Zhanquan Sun et al. 2017	Fake images on the web	95.2	89.45	97.2
Proposed method	**Corn and weeds**	–	–	**98**

The proposed method yielded results with an excellent precision percentage, since it has been proven and it can be seen in the previous table that only two methods out of the 15 reviewed in the state of the art exceed it. A method very similar to the one proposed is the one used by CNN to detect corn diseases. Sibiya [32] detects corn leaf blight disease with 99% accuracy, but detections of the other diseases do not exceed 87%. In the same way, Zhang [33] detects diseases in the corn leaf with an accuracy percentage of 98.9% with the support of advanced models of pre-trained networks such as GoogleNet and data sets with thousands of images such as CIFAR-10 that helped to obtain 98.8% respectively. Therefore, we can mention that the percentage obtained by our method is highly effective with a precision of 98%.

In the Fig. 3, we can see the ROC curve and in the Fig. 4, the area under the curve (AUC) and its values obtained.

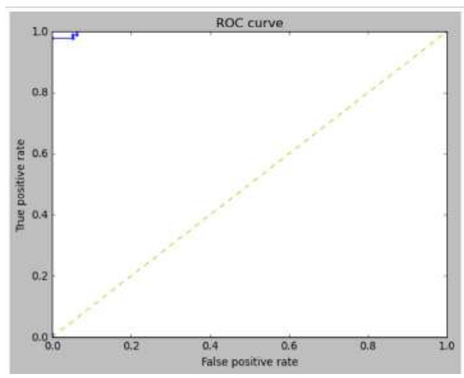

Fig. 3. Graph of the ROC curve.

AUC = 0.9988995598239296

Fig. 4. Value of the area under the curve.

5 Conclusions

The results obtained in the experiments were better than those obtained with the application of the traditional methods reviewed. Therefore, we conclude that a combination of CNN + SVM generates relevant results for the field of image classification by means of convolutional neural networks. The precision obtained by the hybrid algorithm was significant, since the experiment reached 98% precision in the recognition of corn and weeds. The results confirm the performance and reliability of the classifications made by the proposed method. We have demonstrated the efficiency of the system for the recognition of corn and weeds applied to the dataset used.

The method proposed in this research showed better results in terms of precision for the corn and weed image recognition task when compared to what was found in the literature. Overall, we deduce that the CNN model combined with SVM is, in fact, a very promising classification method in the field of corn and weed image recognition. However, it is necessary to extend our Dataset and enrich it to be able to deal with more test images and improve the accuracy rate in validation.

Therefore, the superiority of the proposed method is clearly demonstrated in comparison with the other models of the state of the art. After analyzing the results presented in Table 3, the precision of the CNN + SVM hybrid classifier for the recognition of images of corn and weeds is 98%. The percentage is greater than the image recognition precision shown in said table, thus exceeding 86% of the results shown there.

We conclude that our method obtained the third best performance in the classification of the two classes using its own Dataset. Regarding the two best classification percentages in the table, we can mention in our favor that Sibiya [32] detects the blight disease in the corn leaf with an accuracy of 99%, but the detections of the other diseases do not exceed 87%. In the same way, Zhang [33] detects diseases in the corn leaf with an accuracy percentage of 98.9% with the support of advanced models of pre-trained networks such as GoogleNet and data sets with thousands of images such as CIFAR-10 that helped to obtain 98.8% respectively.

Finally, the collection of images will be promoted to feed the private data set that is available, in order to expand the size and variety of the Dataset. We hope to put the dataset on hand for other researchers for modeling and learning in the future, ultimately wanting to further aid the study in the field. In addition to that, this proposed method can also be used for the classification of images of all kinds, not only for classification of images in the agricultural area.

References

1. INEGI: Gobierno de México. Encuesta Nacional Agropecuaria 2019. “Superficie cultivada y producción de cultivos anuales y perennes por cultivo seleccionado” (2019)
2. Barkin, D.: El maíz: la persistencia de una cultura en México. Cahiers des Amériques latines **40**, 19–32 (2002)
3. Gómez, et al.: Clasificación de plantas de maíz y maleza: hacía la mejora de la fertilización en México. Res. Comput. Sci. **149**(8), 683–697 (2020)
4. Sa, I., et al.: weedNet: dense semantic weed classification using multispectral images and MAV for smart farming. IEEE Robot. Automat. Lett. **3**, 588–595 (2018)
5. Olsen, A., et al.: Deepweeds: a multiclass weed species image dataset for deep learning. Sci. Rep. **9**, 2058 (2019)
6. Chollet, F.: Deep Learning with Python: Fundamentals of Machine Learning. Manning Publications Co., Shelter Island, NY (2018). ISBN 9781617294433
7. Juraszek, G.: Reconhecimento de Produtos por Imagem Utilizando Palavras Visuais e Redes Neurais Convolucionais. UDESC, Joinville (2014)
8. LeCun, Y., Kavukcuoglu, K., Farabet, C.: Convolutional networks and applications in vision. In: Proceedings of 2010 IEEE International Symposium on Circuits and Systems (ISCAS), pp. 253–256. IEEE (2010). https://doi.org/10.1109/ISCAS.2010.5537907

9. Arel, I., Rose, D., Karnowski, T.: Deep machine learning - a new frontier in artificial intelligence research [research frontier]. IEEE Comput. Intell. Mag. **5**(4), 13–18 (2010). https://doi.org/10.1109/MCI.2010.938364
10. Tchangani, A.: Support vector machines: a tool for pattern recognition and classification. Stud. Inf. Control J. **14**(2), 99–109 (2005)
11. Silva, C., Welfer, D., Gioda, F.P., Dornelles, C.: Cattle brand recognition using convolutional neural network and support vector machines. IEEE Latin Am. Trans. **15**(2), 310–316 (2017). https://doi.org/10.1109/TLA.2017.7854627
12. Silva, C., Welfer, D.: A novel hybrid SVM-CNN method for extracting characteristics and classifying cattle branding. Latin Am. J. Comput. LAJC **VI**(1), 9–15 (2019)
13. Niu, X.X., Suen, C.Y.: A novel hybrid CNN-SVM classifier for recognizing handwritten digits. Pattern Recognit. **45**, 1318–1325 (2011). https://doi.org/10.1016/j.patcog.2011.09.021
14. Agarap, A.F.M.: An Architecture Combining Convolutional Neural Network (CNN) and Support Vector Machine (SVM) for Image Classification (2017)
15. Basly, H., Ouarda, W., Sayadi, F.E., Ouni, B., Alimi, A.M.: CNN-SVM learning approach based human activity recognition. In: El Moataz, A., Mammass, D., Mansouri, A., Nouboud, F. (eds.) ICISP 2020. LNCS, vol. 12119, pp. 271–281. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-51935-3_29
16. Constante, P., Gordon, A., Chang, O., Pruna, E., Acuna, F., Escobar, I.: Artificial vision techniques for strawberry's industrial classification. IEEE Latin Am. Trans. **14**(6), 2576–2581 (2016). https://doi.org/10.1109/TLA.2016.7555221
17. Garcia, F., Cervantes, J., Lopez, A., Alvarado, M.: Fruit classification by extracting color chromaticity, shape and texture features: towards an application for supermarkets. IEEE Latin Am. Trans. **14**(7), 3434–3443 (2016). https://doi.org/10.1109/tla.2016.7587652
18. Cervantes, J., Garcia Lamont, F., Rodriguez Mazahua, L., Zarco Hidalgo, A., Ruiz Castilla, J.S.: Complex identification of plants from leaves. In: Huang, D.-S., Gromiha, M.M., Han, K., Hussain, A. (eds.) ICIC 2018, Part III. LNCS (LNAI), vol. 10956, pp. 376–387. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-95957-3_41
19. Yang, C.C., Prasher, S.O., Landry, J.A., Ramaswamy, H.S., et al.: Application of artificial neural networks in image recognition and classification of crop and weeds, 147–152 (2000)
20. Barufaldi, J.M.: Redes neuronales adversarias para el reconocimiento de malezas. Tesis. Facultad de Ciencias Exactas, Ingeniera y Agrimensura. Universidad Nacional de Rosario, Argentina, pp. 47–61 (2016)
21. Haug, S., Andreas, M., Biber, P., Ostermann, J.: Plant classification system for crop/weed discrimination without segmentation. In IEEE Winter Conference on Applications of Computer Vision, pp. 1142–1149 (2014)
22. Hlaing, S.H., Khaing, A.S.: Weed and crop segmentation and classification using area thresholding. IJRET **3**, 375–382 (2014)
23. Amaro, E.G., Canales, J.C., Cabrera, J.E., Castilla, J.S.R., Lamont, F.G.: Identification of diseases and pests in tomato plants through artificial vision. In: Huang, D.-S., Premaratne, P. (eds.) ICIC 2020, Part III. LNCS (LNAI), vol. 12465, pp. 98–109. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-60796-8_9
24. Lanlan, W., Youxian, W.: Weed corn seedling recognition by support vector machine using texture features. African J. Agricu. Res. **4**(9), 840–846 (2009)

25. Campos, Y., Sossa, H., Pajares, G.: Comparative analysis of texture descriptors in maize fields with plants, soil and object discrimination. Precision Agric. **18**(5), 717–735 (2016). https://doi.org/10.1007/s11119-016-9483-4
26. Jiang, H., Zhang, C., Qiao, Y., Zhang, Z., Zhang, W., Song, C.: CNN feature based graph convolutional network for weed and crop recognition in smart farming. Comput. Electron. Agricu. **174**, 105450 (2020). https://doi.org/10.1016/j.compag.2020.105450. ISSN 0168-1699
27. Li, Y., Nie, J., Chao, X.: Do we really need deep CNN for plant diseases identification? Comput. Electron. Agric. **178**, 105803 ((2020). https://doi.org/10.1016/j.compag.2020.105803. ISSN 0168-1699
28. LeCun, Y., Bottou, L., Bengio, Y., Haffner, P.: Gradient-based learning applied to document recognition. Proc. IEEE **86**(11), 2278–2324 (1998)
29. Ahila Priyadharshini, R., Arivazhagan, S., Arun, M., Mirnalini, A.: Maize leaf disease classification using deep convolutional neural networks. Neural Comput. Appl. **31**(12), 8887–8895 (2019). https://doi.org/10.1007/s00521-019-04228-3
30. Cortes, C., Vapnik, V.: Support-vector networks. Mach. Learn. **20**(3), 273–297 (1995). https://doi.org/10.1007/BF00994018
31. Qiao, Y., Cappelle, C., Ruichek, Y., Yang, T.: ConvNet and LSH-based visual localization using localized sequence matching. Sensors **19**(11), 2439 (2019). https://doi.org/10.3390/s19112439
32. Sibiya, M., Sumbwanyambe, M.: A computational procedure for the recognition and classification of maize leaf diseases out of healthy leaves using convolutional neural networks. AgriEngineering **2019**(1), 119–131 (2019). https://doi.org/10.3390/agriengineering1010009
33. Zhang, X., Qiao, Y., Meng, F., Fan, C., Zhang, M.: Identification of maize leaf diseases using improved deep convolutional neural networks. IEEE Access **6**, 30370–30377 (2018). https://doi.org/10.1109/ACCESS.2018.2844405
34. Puente-Maury, L., et al.: Método rápido de preprocesamiento para clasificación en conjuntos de datos no balanceados. Res. Comput. Sci. **73**, 129–142 (2014)
35. Alom, M.Z., Hasan, M., Yakopcic, C., Taha, T.M., Asari, V.K.: Improved inception-residual convolutional neural network for object recognition. Neural Comput. Appl. **32**(1), 279–293 (2018). https://doi.org/10.1007/s00521-018-3627-6