International Journal of Combinatorial Optimization Problems and Informatics, 12(3), Sep-Dec 2021, 98-108. ISSN: 2007-1558.

www.editada.org

Corn plants and weeds classification using the Otsu segmentation method and PCA

Marcos Yamir Gómez Ramos, José Sergio Ruíz Castilla, Farid García Lamont.

Universidad Autónoma del Estado de México, Doctorado en Ciencias de la Computación, Centro Universitario UAEM Texcoco, Texcoco, Estado de México, México.

marcos.yamir@gmail.com, jsergioruizc@gmail.com, fglamont@yahoo.com.mx

Abstract. The corn crop is very important in Mexico. Corn is fertilized manually or with machinery. When fertilization is manual, it consists of depositing fertilizer to each corn plant. Whereas machine fertilization, involve of dropping fertilizer along the furrow continuously. Manual fertilization is effective, but it is expensive and time-consuming. Machine fertilization can be inefficient, because fertilizer is deposited in the weeds or where there is no corn plant. When the fertilizer is not absorbed by the plant, it can damage the aquifers. This project presents algorithms to classify corn plants and weeds, hoping to contribute to automated fertilization or identified weeds to apply herbicide or eliminate. We took hundreds of pictures of corn plants and weeds in corn crops. The images were segmented using the Otsu method. As well as, the images were processed with the PCA algorithm. We apply classification algorithms such as Naive Bayes, Random Forest, SVM, KNN and Backpropagation. We also apply a convolutional neural network (CNN). We finally got 99.97% as the best result with the Backpropagation classifier.

Keywords: Classification, Backpropagation, Segmentation, Corn plants, Weeds, Otsu, PCA.

Article Info
Received Jan 17, 2021
Accepted May 11, 2021

1 Introduction

Corn is very important to Mexico. Corn is representative in the social, cultural and economic aspects. There are two classes of corn in Mexico: white and yellow. The original varieties are 59 in Mexico. Corn production during 2017 was 27.8 million tons in Mexico. The main producers are: Sinaloa 22%, Jalisco 14%, Estado de Mexico 8%, Michoacán 7%, Guanajuato 6%, Guerrero 5%, Veracruz 5%, Chiapas 5%, Chihuahua 4%, Puebla 4% and other 20% are divided among other states. Mexico is the eighth producer in the world [1].

The corn crop must grow without weeds; however, this is not always possible. Weeds must be eliminated by applying herbicides such as Acetochlor or Fluroxipyr 30 days after sowing. Nitrogen fertilizer should be applied 50 to 65 days after sowing. [2]. When the weeds are not removed, the fertilizer is absorbed by the corn plant, but at the same time by the weeds. Wild plants can affect corn growth and production. Fertilizers not absorbed by plants can affect aquifers.

The fertilizers more used are nitrogenous, phosphatic, potassic, and complex fertilizers. The fertilizer not absorbed by the crop plants contaminates the soils and aquifers. Chemical fertilizers also pollute the water, affecting aquatic flora and fauna. The amount of fertilizer must be balanced with the demand of the crop, to avoid contamination by excess [9].

A corn farmer spends up to 1,700 dollars per hectare in each harvest cycle in Sinaloa, Mexico. Growing corn requires an investment in fertilizer of up to 60% [3]. It would be better to employ artificial vision algorithms for the classification of corn plants and weeds. We pretend to contribute to the possible improvement in the fertilization process, reduction of contamination in aquifers and reduction of production costs for corn farmers.

2 State of the Art

At this time, computer science seeks to solve problems in our environment, some problems include digital image processing and machine learning among many others. This research work is focused on the agricultural study area. We propose the classification of corn plants and weeds using artificial vision.

The computer vision algorithms at this stage have been implemented in multiple fields such as agriculture. Some examples are detection of fruits [4], classification of plants [5] and classification of plants from images of leaves [6], in addition to crop disease classification [7] and weeds recognition [8]. The above, has a direct impact on crop production. The farmer can get a cost during production. Consequently, computing has contributed to problem-solving in agriculture. However, there are still pending issues.

The identification and classification of plants are not easy, this problem has been solved by several researchers. Researchers have implemented characteristics extraction and selection techniques, taking into account the color, shape and texture of the plants or leaves. There are used machine learning algorithms [5,6,11,12].

Previous contributions in the field of image segmentation considering color and grayscale. Image segmentation is a great opportunity for researchers in controlled and uncontrolled environments. Moreover, we have reviewed in-depth related works on the segmentation of color images [13]. Similar works [8] have been segmented totally with fully connected neural networks (FCNN).

The literature review shows that disease detection has been developed in different plants, using "feature extraction techniques (GWT)" and classifying with support vector machines (SVM) [14]. Added to this, the trend of the implementation of deep learning has taken a lot of force seeking to solve problems from different disciplines. CNN neural networks have been used for the detection of diseases and pests in tomato plants [15]. In other cases, using deep learning techniques such as machine learning collaborating for the same purpose [16]. In addition to the development of robotic systems applying artificial vision methods [17].

An artificial vision algorithm allows to identify different types of weeds to apply the herbicide for each type of weed. Weed identification required visual, shape, spatial, and spectral characteristics. Some results were 92.9% with KNN, 85% with K-means clustering, 95.7% with Rest-Net-50, 97% with SVM among other results [10].

Corn plants and weeds classification have been achieved by a vector data description using the color index. The color is notably similar in corn plants and weeds, which makes its identification a difficult process. PCA made it possible to reduce shine and improve results. The results obtained after three years were 93.87% in outdoor fields [18].

Convolutional Neural Networks (CNN) have been applied to classify corn plants and weeds. The photographs were obtained and classified. CNN's are capable of segmenting and classifying images. The architectures used for the classification were: LeNET, AlexNet, cNET and sNET. The solution has been configured to be applied in the outdoor field in crops in Ecuador. The best results were obtained with cNET using 16 filters [19].

Obstacle detection in a crop field has been proposed. A tractor can tow machinery in open fields, but it is necessary to detect obstacles. Segmentation was necessary taking into account color and texture. The solution is proposed to work in real-time, so it is important to detect movement. Major changes indicate an obstacle. It would imply an action of the machinery [32].

The identification of crops and weeds was possible using the SVM technique. The goal was to identify crops, soils, and weeds. Crop and weeds recognition certainly allows for various future applications. The proposal achieved 94.3% accuracy in identifying three categories: crops, soil and weeds. The solution could be used in autonomous vehicles and tractors [33].

In the proposed system, has been used a laptop computer with medium-level characteristics. The above, because the application is considered to be built for use in a real, web or mobile environment.

3 Methodology

The proposed solution allows the identification of corn plants and weeds, using image processing techniques, feature extraction and artificial intelligence algorithms. The algorithms contribute to the efficiency in the application and use of fertilizers in corn crops in Mexico. The solution could also reduce economic losses for farmers. The proposal could finally avoid the contamination of soils and aquifers. The adopted method is represented by three modules, processing, feature extraction and classification, as suggested [20]. The algorithms implemented in this work have been coded in Matlab R2019, while CNN was coded in the Python version (3.5). This work has been carried out on a laptop with the following characteristics: MacBook Pro, Intel Core i5 processor, 2.6 GHz and 8 GB of RAM memory.

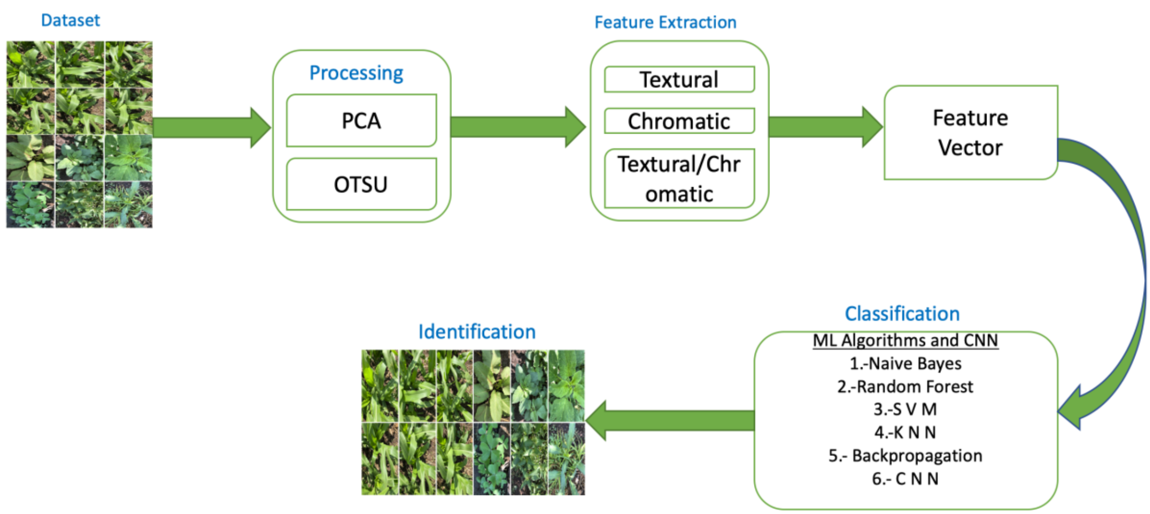


Fig. 1. Methodology used.

The dataset images were segmented to proceed with the extraction of characteristics. On the other hand, the Dataset images were processed with PCA to reduce the dimensionality, then the extraction of features was continued. The extraction of characteristics allowed to obtain a vector of characteristics. The feature vector was classified by the algorithms of: Naive Bayes, CNN, Random Forest, SVM, KNN and Backpropagation. Finally, the results were obtained.

3.1 Segmentation

The Dataset was processed using the adaptive edge segmentation algorithm, threshold value method (Otsu) during experimentation [21] [22]. Furthermore, we use Principal Component Analysis (PCA) for dimension reduction [17]. PCA is used to minimize linear correlations between variables and maximize the entropy of the information in different main extractions. PCA is a feature-specific selection technique that uses an orthogonal transformation to convert a set of observations of variables, possibly correlated, into a smaller set of variables that are no longer correlated [17].

Otsu is a digital image binarization technique widely used in artificial intelligence, especially when using real images taken in indoor fields. Otsu is adapted to various conditions and is based on statistical concepts, specifically the variance is used as a measure of dispersion of values (dispersion of gray levels). The objective of the method is to calculate the threshold value, so that the dispersion within each class is as small as possible, but at the same time that the dispersion is as high as possible among different classes. Another important feature of Otsu is that it is an unsupervised method, it is automatic and it does not require human supervision or prior image information.

The images of plants of corn and weeds were successfully segmented using the following steps: 1) it was calculated high-contrast grayscale from the optimal linear combination of color components RGB [21,22]; 2) There was estimated the optimal boundary by running the adaptive edge segmentation algorithm Otsu [21,22] and a phase of the principal component analysis PCA [17]; 3) there were applied morphological operations to fill possible empty spaces in the segmented image [21,22]. The method did allow to obtain the best segmentation even with changes in the brightness conditions. The method to segment the image, can use only the region of the sheets, determine their edges, and calculate properties by extracting features [5].

3.2 Feature extraction

Feature extraction is considered crucial within machine learning algorithms. Feature extraction methods define the descriptors used for the recognition of corn and weeds. The most widely used feature extraction methods are: extraction of geometric, textural and chromatic features. Images have many features, which are extracted and added to a vector of image features. When an image is successfully segmented, it focuses on the region of interest and calculates the properties by extracting features. In this work, we extracted textural and chromatic features, in addition to a combination of these.

Textural Characteristics: The characteristics can have properties namely: rugged, rough and smooth, among other characteristics. The texture is invariable to displacement because it repeats a pattern on a surface. Perception is relative, so it is necessary to explain why the visual perception of a texture is independent of a visual position. Textural features are extracted from the surfaces of corn plant leaves and weed leaves. It was implemented the Haralick algorithm [23]. Additionally, the matching matrices with gray levels were used.

Chromatic Characteristics: Color characteristics provide a lot of information and can be extracted from a specific color space. The colors are obtained starting from three primary channels such as RGB, hue saturation value HSV and grayscale among others. Also, it is required to locate descriptors by means of different algorithms, considering: Hu moments, Fourier descriptors, and discrete cosine transform (DCT), similarly, Gabor characteristics. Hu moments [24] integrate information from the color variable of the region of interest in 2D. The DCT uses base transformations and cosine functions of different wavelengths. The DTC has a particularity in relation to the discrete Fourier transform DFT, is the limitation in the use of real coefficients. The Gabor characteristics [25] is considered a robust technique used for the extraction of characteristics in images, being a hybrid technique composed of the Fourier transformation nucleus in a Gaussian function.

3.3 Classification

The following algorithms for the tests were implemented: 1) in the first experiments, Matlab was employed with the Weka environment (Waikato Environment for Knowledge Analysis). Naive Bayes was tested, Random Forest, SVM, KNN, and Backpropagation. 2) the second process, it was carried out tests in Python with the CNN algorithm.

Naive Bayes: Bayesian classifiers are based on Bayes decision theory. Bayes' principle provides a fundamental methodology for solving pattern classification problems when the probability distribution of the patterns is known. A Bayesian classifier uses a probabilistic approach to assign the class to an example [26].

Random Forest RF: Random forest is an algorithm composed of decision tree classifiers, each tree depends on the values of a random vector with independent sampling and with the same distribution for all trees in the forest. The generalization error for forests converges to a limit, as the number of trees in the forest increases. When a model generalizes and fails, it depends on the strength of the individual trees in the forest and the correlation between them [27].

SVM: Support Vector Machines (SVM) is a classification technique widely used in recent years. The essential points of SVM are: the use of kernels when working with non-linear sets, the absence of local minima, the solution depends on a small subset of data and the discriminative power of the model obtained by optimizing the separability margin between classes. These characteristics allow SVMs to obtain very competitive results compared to other classifiers [28].

KNN: The KNN algorithm classifies a new point in the data set based on the Euclidean distance, finding the k closest distances to the object to be classified, then the class of the closest point in the data set is assigned by majority vote. The process is repeated *n* times [29].

ANN Backpropagation: Humans, to solve problems of daily life, take previous knowledge acquired from the experience of a specific area. In the same way, artificial neural networks collect information on solved problems to build models or systems that can make decisions automatically. The multiple connections between neurons form an adaptive system whose weights are updated by a particular learning algorithm. Of the different learning algorithms of artificial neural networks, it was chosen to use the Backpropagation algorithm. This algorithm performs the learning and classification process in four points: initialization of weights, forward propagation, backward propagation and update of weights [30].

CNN: Convolutional Neural Networks are a type of neural network focused on the process of classifying images, text, audio and speeches. CNN's are inspired by multi-level perceptron networks. CNN allows a convolution by means of a 3x3 or 5x5 filter on the matrix of pixels of the image row by row until the entire image is crossed, to apply a RELU activation and pooling. As a result, a new matrix is obtained to which a convolution can be applied again. It is called deep learning because multiple convolutions can be applied. After applying the convolutions, a completely connected network is obtained that can be classified by a function such as softmax. For this work, we have used Python and the Keras and TensorFlow libraries.

The CNN required two data sets, in this case, 800 images were taken for training and 200 for validation. We applied cross-validation with 5 k-folds of images that resulted in 97% effectiveness [31]. The architecture of a CNN is shown in the following figure:

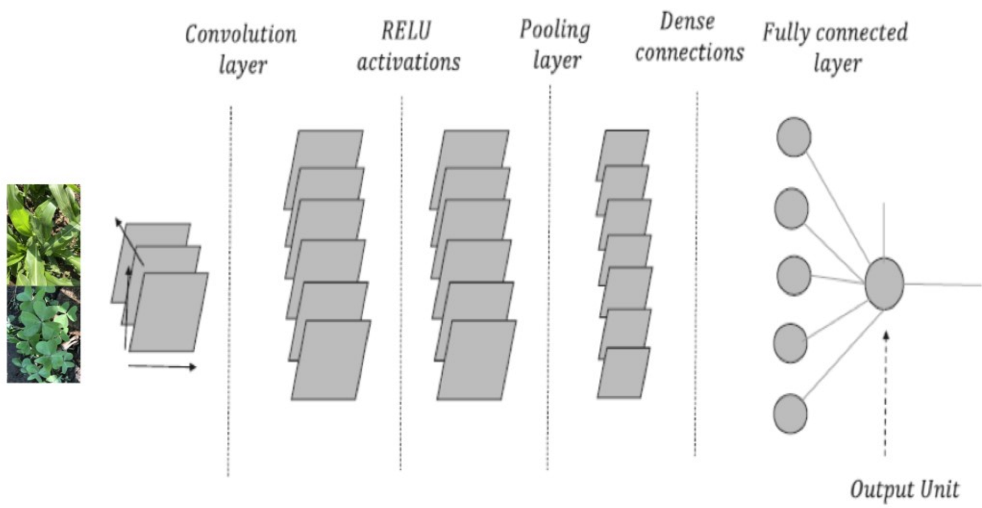


Fig. 2. CNN architecture

4 Results

In this section, the Dataset that was used for the experimentation is described. The percentages obtained in the experimentation tests. In this process, the process applied the segmentation methods and classification algorithms above mentioned.

4.1 Dataset

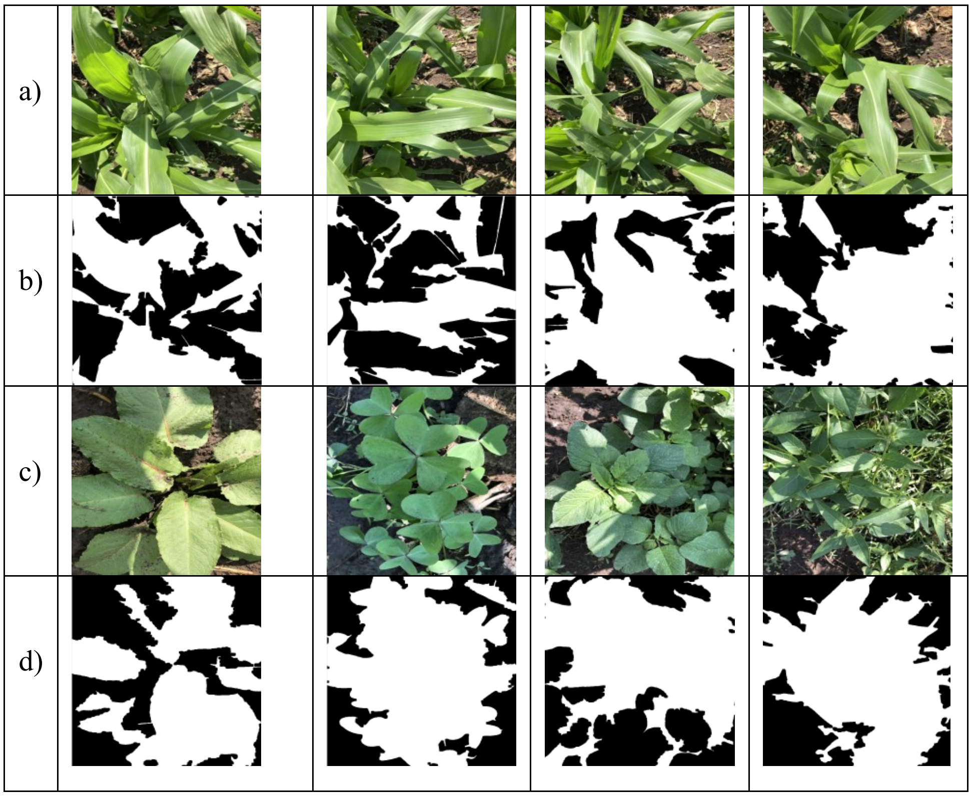
It was difficult to find a specific Dataset for corn plants and weeds with the necessary characteristics for this work. The images found in the Internet databases did not meet the desired characteristics. Other databases contain insufficient images. Therefore, we created our Dataset that includes 1000 high-resolution images. Those images were used for training and testing in Matlab and Python. All the photographs were taken in the outdoor field. We took 1000 photos for training and testing using an iPhone 8 plus cell phone with a 12-megapixel camera and a selfie stick.

Table 1. Dataset characteristics.

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

Table 2 shows the images taken from above. The photos correspond to corn plants as well as diverse weeds. The images were segmented through the Otsu method. The segmentation was done with the Otsu. We applied the PCA method. The segmented images were used to carry out the classification of corn plants and weeds.

Table 2. Images used in the experimentation: a) corn plants, b) segmented corn plants, c) weeds, d) segmented weeds.



Textural characteristics
The descriptors used by Haralick extract 84 features in total, 28 for each RGB color channel (28x3 = 84). They described below:

1.- Second angular momentum.	2.-Contrast
3.- Correlation	4.-Sum of squares
5.-Moment of inverse difference	6.-Average sum
7.-Sum of variance	8.-Sum of entropy
9.-Entropy	10.-Difference of variances
11.-Entropy difference	12.-Correlation measure I
13.-Correlation measure II	14.-Max. Correlation coefficient.

The average and a range are extracted so it is double, that is, two values for each characteristic.

Chromatic characteristics

GABOR algorithm was executed with a total of 201 features which were extracted in total, 67 for each RGB color channel (67x3 = 201). Implementing intensity Hu Moments to extract 21 features in total, 7 for each RGB color channel (7x3 = 21).

Furthermore, DCT characteristics were extracted (Discrete Cosine Transform) which were 12 in total, 4 for each RGB color channel (4x3 = 12), 24 characteristics with Fourier Descriptors, 8 for each RGB color channel (8x3 = 24), 15 contrast characteristics and 5 for each RGB color channel (5x3 = 15).
Finally, a total of 357 characteristics were obtained in each image, of which 84 were textural and 273 chromatic.

Parameters and hyper-parameters of the classification algorithms

We use the parameters and hyper-parameters that come by default in Weka

Naive Bayes: batchsize = 100, numDecimalPlaces = 2, and Cross-validation = 10 folds.

Random Forest: bagsize = 100, batchsize = 100, maxDepth = 0, numDecimalPlaces = 2, numExecutionSlots = 1, numFeatures = 0, numIterations = 100, seed = 1, and Cross-validation = 10 folds.

KNN: knn = 1, batchsize = 100, numDecimalPlaces = 2, windowsSize = 0, and Cross-validation = 10 folds.

SVM: batchsize = 100, c = 1.0, epsilon = 1.0E-12, numDecimalPlaces = 2, numFolds = -1, randomseed = 1, toleranceParameter = 0.001, and Cross-validation = 10 folds.

Backpropagation: batchsize = 100, hiddenLayers = a, learningRate = 0.3, momentum = 0.2, numDecimalPlaces = 2, seed = 0, trainingTime = 500, validationSetSize = 0, validationThreshold = 20, and Cross-validation = 10 folds.

4.2 Experimental Results

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

Table 3 shows the results obtained when applying the PCA method with the extraction of textural characteristics, as well as the comparison of the classification algorithms used. In this case, the best percentage of precision has been obtained with the Backpropagation technique. The precision was 98.78%.

Table 3. Results with PCA method and textural features.

Algorithm	ACC	S	E	P	R	F-m	MCC
Naive Bayes	78.44	90.9	65.8	80.3	78.4	78.1	58.7
Random Forest	93.11	96.1	90	93.3	93.1	93.1	86.4
SVM	93.21	96.9	89.4	93.5	93.2	93.2	86.7
KNN	93.62	96.7	90.4	93.8	93.6	93.6	87.4
Backpropagation	**98.78**	98.9	98.5	98.8	98.8	98.8	97.6

Table 4 shows the results obtained by using the Otsu segmentation method with the extraction of textural characteristics and the comparison of the classification algorithms used. In this case, the best percentage of precision has been obtained with the Backpropagation technique. The precision was **98.98**%.

Table 4. Results with Otsu segmentation and textural features.

Algorithm	ACC	S	E	P	R	F-m	MCC
Naive Bayes	77.3	89.8	64.7	79.2	77.3	76.9	56.4
Random Forest	91.9	94.1	89.7	92	91.9	91.9	83.9
SVM	95.6	97.5	93.5	95.6	95.6	95.6	91.2
KNN	93.2	95.5	90.9	93.3	93.2	93.2	86.6

Backpropagation	**98.98**	98.7	99.1	99	99	99	98

Table 5 shows the results obtained by using the PCA method with the extraction of chromatic characteristics and the comparison of the classification algorithms used. Likewise, the best percentage of precision has been obtained with the Backpropagation technique. The precision was 97.8%.

Table 5. Results with PCA segmentation and chromatic features.

Algorithm	ACC	S	E	P	R	F-m	MCC
Naive Bayes	77	91	62	77	77	76.5	56.3
Random Forest	93.9	90	94	93.9	93.9	93.9	88
SVM	94.8	97	92	94.9	94.8	94.8	89.7
KNN	94.8	97	92.6	94.9	94.8	94.8	89.7
Backpropagation	**97.8**	98.6	97	97.8	97.8	97.8	95.6

Table 6 shows the results obtained by using the Otsu segmentation method with the extraction of chromatic characteristics and the comparison of the classification algorithms used. Again, the best percentage of precision has been obtained with the Backpropagation technique. The precision was 97.9%.

Table 6. Results with Otsu segmentation and chromatic features.

Algorithm	ACC	S	E	P	R	F-m	MCC
Naive Bayes	79	89	62	79	79	78.7	60
Random Forest	93.2	95.8	90	93.3	93.2	93.2	86.5
SVM	96.4	98.6	94.2	96.5	96.4	96.4	92.9
KNN	94.2	97.2	91.2	94.4	94.2	94.2	88.6
Backpropagation	**97.9**	98.6	97.2	97.9	97.9	97.9	95.8

Table 7 shows the results obtained when using the PCA method with the extraction of hybrid characteristics, that is, a combination of textural and chromatic characteristics. Continuing with the same comparison of classification algorithms used. The precision was 98.58%.

Table 7. Results with PCA method and hybrid features.

Algorithm	ACC	S	E	P	R	F-m	MCC
Naive Bayes	78	91.2	63	80.4	78	77.6	58.3
Random Forest	94.73	96.6	90.6	94.9	94.7	94.7	89.6
SVM	97.57	97.8	95	97.6	97.6	97.6	95.2
KNN	94.53	97.6	89.6	94.7	94.5	94.5	89.3
Backpropagation	**98.58**	98	96.8	98.6	98.6	98.6	97.2

Table 8 shows the results obtained when using the Otsu segmentation method with the extraction of hybrid characteristics, that is, a combination of textural and chromatic characteristics; continuing with the same comparison of classification algorithms used. The precision was 98.89%.

Table 8. Results with Otsu segmentation and hybrid features.

Algorithm	ACC	S	E	P	R	F-m	MCC
Naive Bayes	78.68	89	66	80	68	78.4	59.2
Random Forest	93.63	94.6	90.8	93.7	93.6	93.6	87.4
SVM	98.38	98.2	96.6	98.4	98.4	98.4	96.8
KNN	94.64	95.6	91.8	94.7	94.6	94.6	89.4
Backpropagation	**98.89**	97.8	98	98.9	98.9	98.9	97.8

The Table 9 shows the percentage of accuracy obtained when doing the test with a convolutional neural network. These results are displayed independently of the other Dataset shown in the previous tables. In this case, we do not apply a previous segmentation process. We did tests with segmented images and got poor results. Afterwards, tests were applied with the unsegmented images and obtained better results. Therefore, training and testing were performed with the original unsegmented images and the data was not normalized, this is the reason why Backpropagation surpasses CNN in the percentage.

Table 9. Results with Convolutional neural network (CNN).

Algorithm	ACC	S	E	P	R	F-m	MCC
CNN	97	100	92	96	96	96	95.4

Cross-validation was applied, using 5 k-Folds working with 1000 images. 80% of images were used for training. 20% of images were used for validation. After carrying out the cross-validation, the results of Table 9 were obtained. In Table 10 it can be observed the results obtained in each validation test. The average of the results obtained shows that a precision of 93% was achieved.

Table 10. Results with Cross-validation.

K-Fold	TP	FP	FN	TN	ACC	S	E	P	F1
1	93	7	1	99	0.96	0.99	0.93	0.93	0.96
2	97	3	1	99	0.98	0.99	0.97	0.97	0.98
3	84	16	5	95	0.89	0.95	0.84	0.85	0.89
4	97	3	0	100	0.98	1.00	0.97	0.97	0.98
5	95	5	3	97	0.96	0.97	0.95	0.95	0.96
Average					**0.95**	**0.98**	**0.93**	**0.93**	**0.95**

Figure 3 presents a graph displaying the best results of the research, showing that the best segmentation method used was Otsu, using the extraction of characteristics (textural, chromatic and hybrid) and the best algorithm that yielded the percentages at sight. The green bar represents the results of the tests performed with the Otsu segmentation method and the extraction of textural features, showing the highest precision obtained with the 98.99% Backpropagation algorithm. The orange bar presents the results in the tests carried out with the Otsu segmentation method and the extraction of hybrid characteristics (textural and chromatic), showing the highest precision also obtained with the Backpropagation algorithm 98.89%. The blue bar shows the results in the tests carried out with the Otsu segmentation method and the extraction of chromatic characteristics, as in the previous cases, it shows the highest precision obtained with the 97.9% Backpropagation algorithm. The purple bar shows the percentage of effectiveness using the convolutional neural networks CNN that obtained 97% accuracy during the training. Finally, the gray bar shows a precision of 93% with cross-validation.

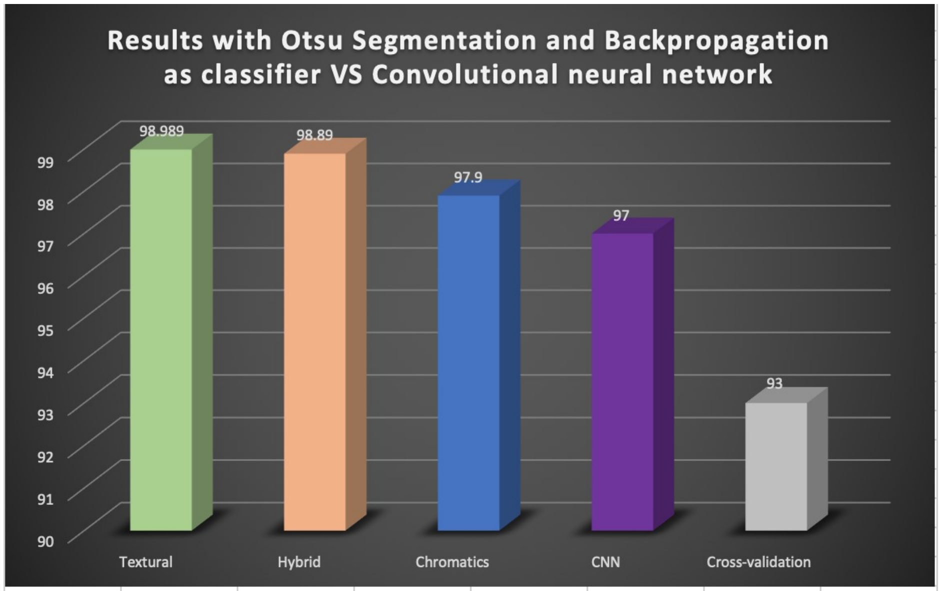


Fig. 3. Results graph with the best precision.

The results obtained from the CNN is not better because the images were incorporated without pre-processing of images and the values of the data were not normalized. The images were used as like as was obtained from the outdoor field.

5 Conclusions

The test was completed with the Dataset of 1000 images of corn plants and weeds, using PCA method and Otsu segmentation method. The classification was applied; using Naive Bayes, Random Forest, SVM, KNN, CNN and Backpropagation techniques to obtain classification results. The classification algorithms showed the best results ranging from 97% to 98.98% accuracy in the classifications of corn plants and weeds. This allows determining that the best technique was Otsu segmentation with extraction of textural characteristics and the use of the Backpropagation algorithm, since it yielded a 99% precision. Therefore, it can be very effective in implementing corn plant detection technologies for automated fertilization. Another possible uses can be to apply herbicide. The artificial vision and machine learning techniques, accompanied by mechatronics tools, could be implemented in the current fertilization process in Mexico. Precise identification of corn plants and weeds can help to: implement automated fertilization, identify weeds for elimination, identify weeds to apply herbicides and ultimately decrease contamination of aquifers.

References

1. Gobierno de México. Agencia de servicios a la comercialización y desarrollo de mercados agropecuarios. Maíz grano cultivo representativo de México. https://www.gob.mx/aserca/articulos/maiz-grano-cultivo-representativo-de-mexico?idiom=es
2. Ibrahim E. Soliman 1 and H.S. Gharib, "Response of weeds and maize (zea mays l.)To some weed control treatments under different nitrogen fertilizer rates", Zagazig J. Agric. Res., Vol. 38 No. (2) pag 249-271, 2011
3. Silva, A.R.E., Cobelas, M.A., González, E.M.: "Impactos del nitrógeno agrícola en los ecosistemas acuáticos. Revista Científica de ecología y medio ambiente". Ecosistemas 26(1), 37-44. (2017)
4. 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 America Transactions 14(7), 3434-3443 (2016). doi:10.1109/tla.2016.7587652
5. Cervantes, J., Taltempa, J., García-Lamont, F., Castilla, J.S.R., Rendón, A.Y., Jalili, L.D.: "Análisis comparativo de las técnicas utilizadas en un sistema de reconocimiento de hojas de planta". Revista Iberoamericana de Sistemas e Informática Industrial RIAI 14(1), pp. 104–114. (2017). doi: 10.1016/j.riai.2016.09.005
6. Niño, D.A., Castilla, J.S.R., Zenteno, M.D.A., Jalili, L. D.: "Complex leaves classification with features extractor". pp. 758–769. (2019). doi:10.1007/978-3-030-26969-2_72
7. Zhang, S.,Wang, X.,Wang, Z.: "Weed recognition in wheat based on sparse representation classification". In: Intelligent Computing Theories and Application Springer International Publishing. pp. 511-519. (2019).

8. Wang, X.F., Wang, Z., wen Zhang, S.: "Segmenting crop disease leaf image by modified fully-convolutional networks". pp. 646–652. (2019). doi:10.1007/978-3-030-26763-6_62
9. Khan, M. N., Mobin, M., Abbas, Z. K., & Alamri, S. A. "Fertilizers and their contaminants in soils, surface and groundwater". Encyclopedia of the Anthropocene, 5, 225-240. (2018).
10. Sohail, R., Nawaz, Q., Hamid, I., Gilani, S. M. M., Mumtaz, I., Mateen, A., & Nawaz, J. "A review on machine vision and image processing techniques for weed detection in agricultural crops". Pakistan Journal of Agricultural Sciences, 58(1). (2021).
11. Jalili, L.D., Morales, A., Cervantes, J., Ruiz-Castilla, J. S.: "Improving the performance of leaves identification by features selection with genetic algorithms". pp. 103–114. (2016). doi:10.1007/978-3-319-50880-1_10
12. Cervantes, J., Lamont, F.G., Mazahua, L.R., Hidalgo, A.Z., Castilla, J.S.R.: "Complex identification of plants from leaves". pp. 376–387. (2018). doi:10.1007/978-3-319-95957-3_41
13. Garcia-Lamont, F., Cervantes, J., López, A., Rodriguez, L.: "Segmentation of images by color features: A survey". *pp.* 1–27. (2018). doi: 10.1016/j.neucom.2018.01.091
14. Prasad, S., Kumar, P., Hazra, R., Kumar, A.: "Plant leaf disease detection using Gabor wavelet transform". pp. 372–379. (2012). doi:10.1007/978-3-642-35380-2_44
15. Fuentes, A., Yoon, S., Kim, S., Park, D.: "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition". pp. 17(9), 2022. (2017). doi:10.3390/s17092022
16. Shijie, J., Peiyi, J., Siping, H., Liu Haibo.: "Automatic detection of tomato diseases and pests based on leaf images". (2017). doi:10.1109/cac.2017.8243388
17. Schor, N., Bechar, A., Ignat, T., Dombrovsky, A., Elad, Y., Berman, S.: "Robotic disease detection in greenhouses: Combined detection of powdery mildew and tomato spotted wilt virus". *pp.* 354–360. (2016). doi:10.1109/lra.2016.2518214
18. Yang Zheng, Qibing Zhu, Min Huang, Ya Guo, and Jianwei Qin. 2017. "Maize and weed classification using color indices with support vector data description in outdoor fields". Comput. Electron. Agric. 141, 215–222. C (September 2017). DOI:https://doi.org/10.1016/j.compag.2017.07.028
19. C. Andrea, B. B. Mauricio Daniel and J. B. José Misael, "Precise weed and maize classification through convolutional neuronal networks," 2017 IEEE Second Ecuador Technical Chapters Meeting (ETCM), Salinas, Ecuador, pp. 1-6, 2017. doi: 10.1109/ETCM.2017.8247469.
20. 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". (2020). doi:10.1007/978-3-030-60796-8_9
21. Gonzalez, R.C., Woods, R.E., Eddins, S.L.: "Digital image processing using MATLAB". Pearson Education India. (2004).
22. Sonka, M., Hlavac, V., Boyle, R.: "Image Processing, Analysis and Machine Vision". (1993). doi:10.1007/978-1-4899-3216-7
23. Haralick, R.M., Shanmugam, K., Dinstein, I.: "Textural features for image classification. IEEE Transactions on Systems, Man, and Cybernetics SMC-3". (6), pp. 610-621. (1973).
24. Hu, M.K.: "Visual pattern recognition by moment invariants. IEEE Transactions on Information Theory" 8(2), pp. 179–187. (1962). doi:10.1109/tit.1962.1057692
25. Gabor, D.: "Theory of communication: Journal of the institute of electrical engineers", 93, pp 429–457. (1946).
26. John, G.H., Langley, P.: "Estimating continuous distributions in Bayesian classifiers". Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence. (1995).
27. Breiman, L.: "Random forests. Machine learning". *pp.* 45(1), 5–32. (2001). doi:10.1023/A:1010933404324
28. Vapnik, V.: "An overview of statistical learning theory. IEEE Transactions on Neural Net-works". *pp.* 10(5), 988–999. (1999). doi:10.1109/72.788640
29. Aha, D.W., Kibler, D., Albert, M. K.: "Instance-based learning algorithms. Machine Learning". *pp* 6(1), 37–66. (1991). doi:10.1007/bf00153759
30. Rumelhart, D.E., Hinton, G.E., Williams, R. J.: "Learning representations by back-propagating errors". *pp*. 533–536. (1986). doi:10.1038/323533a0
31. Santanu Pattanayak.: "Pro Deep Learning with TensorFlow". Bangalore, Karnataka, India. Library of Congress. (2017). doi:10.1007/978-1-4842-3096-1
32. Yerania Campos, Humberto Sossa, and Gonzalo Pajares. 2016. "Spatio-temporal analysis for obstacle detection in agricultural videos". Appl. Soft Comput. 45, C 86–97. (August 2016), DOI:https://doi.org/10.1016/j.asoc.2016.03.016
33. Campos, Y., Sossa, H. & Pajares, G. "Comparative analysis of texture descriptors in maize fields with plants, soil and object discrimination". Precision Agric 18, 717–735 (2017). https://doi.org/10.1007/s11119-016-9483-4