# Recognition of Bean Plants in Weeds using Neural Networks

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*Abstract:* - The implementation of a random subspace classifier (RSC) neural network for the recognition of bean plants in weeds was proposed. The RSC neural classifier is based on the multilayer perceptron with a single layer of training connections, allowing a high speed training. The input of this classifier can be considered in various modes, for example, histograms of brightness, contrast, and orientation of micro contours. The RSC neural classifier has been developed for recognition and is applied to different tasks such as micromechanics, tissue recognition, and recognition of metallic textures. The RSC application can help automatize the industrial processes in agriculture. For this purpose, the computer vision based on neural networks can be used.

*Key-Words:* -Neural Networks, Computational Intelligence Systems, RSC neural classifier, Computer vision

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## 1 Introduction

Several studies have focused on class recognition using different types of techniques, such as the Bayesian probabilistic classifier [1]. This probabilistic technique is generally used because of its classification properties and speed. The main objective is to minimize the error with the help of a priori knowledge of the density functions of the classes to be classified [2]. Sometimes the support vector machine (SVM) is used for recognition, and it is more efficient compared to other methods. It can be performed for fewer samples, which makes the classifier very popular [3], [4]. Similarly, there are problems of classification in which the random subspace classifier (RSC) method is used [5]. This RSC classifier works with the characteristics of the images, for example, the brightness histogram, contrast histogram, and histogram of an orientation of micro contours.

The RSC neuronal classifier has been developed for recognition and is applied in different tasks such as micromechanics, tissue recognition in medicine, and recognition of metallic textures [5]. Since the past few decades, computer methods have been increasingly used in agriculture. The problem of recognition of pests that affect crops is actual and interesting worldwide. The recognition of pests in potato and bean fields (Colorado beetles for potato and Mexican beetles for bean) was previously performed using the RSC neuronal classifier. Different experiments were carried out, varying the structure and input parameters of the RSC neural classifier to identify the appropriate parameters to obtain better results in defining the classes. For this recognition task, it was possible to obtain a good recognition rate of 82 % [6].

Different neural classifiers have been developed by researchers for image recognition tasks. These include limited receptive area (LIRA) neural classifiers and permutated coding neural classifiers (PCNC) [7]–[11].

In this work, the possibility to recognize a bean plant in weeds was considered. Using a neural classifier it was possible to design a system capable of recognizing two classes, bean plant and weeds.

One of the factors that causes a drop in the yield of the bean crop in central Mexico is the presence of weeds, which can incur losses of up to 80 % in the yield. In Mexico, 50 types of weeds exist. In addition, this can increase the cost of the harvest and diminish the quality of the product [12].

Weeds are a problem, and it is difficult to establish a general system that allows its prevention. However, there are some general principles that can be applied. For this, it is necessary to consider land preparation, intercropping (plantations of two types of crops), and chemical control [13]. These require the development of an automated system for the application of chemicals (pesticides) to prevent the weed growth.

Last decade a weed detection using computer vision, machine learning and artificial intelligence methods are very popular themes of investigations [14] - [17]. Design of autonomous vehicles for precision agriculture motivates the engineers to develop new sensors and recognition methods [18].

Currently there are agricultural companies that are dedicated to recognition in the area of agriculture. Blue River Technology's goal is to help farmers save on pesticide spraying. Using machine learning, they developed a system based on artificial intelligence capable of identifying and spraying pesticides on the herbs that affect the harvest; consequently, it is possible to save considerable pesticide, achieving a significant cost reduction [19]. The company "John Deere" paid US $305 million to stay with the American Blue River Technology, a leading company working on artificial intelligence applied to precision agriculture.

The "See & Spray," the latest innovation of the Blue River Technology, has become one of the most advanced weed detectors presently.

Cameras and artificial intelligence systems are combined to reduce herbicide usage by up to 90 %. Each plant is analyzed and compared to a library of images to determine if it is a weed and make selective application of pesticides.

"John Deere" emphasizes the policy of incorporating state-of-the-art technologies into its global business through business acquisitions and strategic alliances. Fig.1 shows the R120 tractor [20].

Fig. 1: R120 (manufactured by the John Deere company) in the field [20]

R120 is a Hybrid Retro boom. It passes easily with 60-foot (18.28m) boom folds.

## 2 RSC Neural Classifier

The RSC classifier is based on a multilayer neural classifier and is developed on the basis of the random threshold classifier (RTC), a neuronal classifier [5]. The main feature of the RSC includes a single matrix of training connections between the penultimate and ultimate layers of the classifier, which allows high speed training. For training, the Hebb's rule is used for modifying weights. Thus, we modified the weights of the connections between the ultimate and penultimate layers (Fig.2).

The neuron output function $y$ is calculated as:

$$y = f(S - \theta) , \quad (1)$$

where $\theta$ is threshold of the neuron and $S$ is calculated as:

$$S = \sum_{i=1}^{M} w_i x_i \quad (2)$$

where $x_i$ is the input signal, $w_i$ is the connection weight.

The input characteristics are obtained from the image and can be calculated using different algorithms, for example, the brightness, contrast, color, and contour histograms. It should be noted that the characteristics extracted from the image depend on what is to be classified. When the characteristics ($X_1$, $X_2$,…, $X_n$) of each image are extracted, they are input to all the nonmodifiable neural blocks, which are structured in the form of several layers of neurons with specific functions.

The first layer consists of two neurons: a "high" neuron and a "low" neuron with thresholds $h_{ij}$ and $l_{ij}$, respectively, where $i$ represents the characteristic number and $j$ represents the neuronal group number [5]. These neurons have the activation thresholds, which is selected randomly, considering the condition that the threshold of $l$ is always less than that of $h$ ($l < h$) (Fig.2).

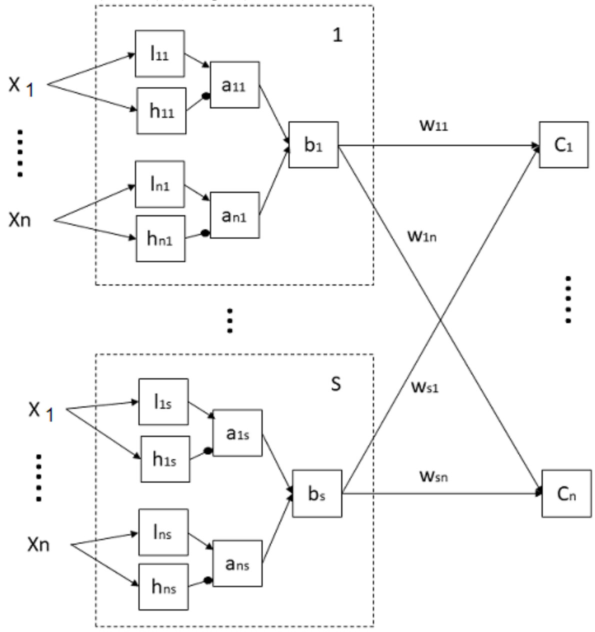


Fig. 2: Structure of the RSC classifier

Neurons $l$ and $h$ are connected to the next $A$ layer of neurons $a_{ij}$; neuron $l$ is connected with exited connection, and neuron $h$ is connected with inhibitory connection. If the value of any input characteristic exceeds the threshold value $l$ and is less than $h$, neuron $a$ is activated giving an output value of 1, otherwise the output value is 0. This indicates that the characteristics of the image must lie between the thresholds of $l$ and $h$ neurons, giving the neurons output a value of 1 if this criterion is satisfied or a value of 0 otherwise. Subsequently, the $a_{ij}$ neurons are connected to a layer of $b_j$ neurons, which correspond to the output of the neural group, and its activation is possible if and only if all the $a_{ij}$ neurons have values equal to 1 [5].

The neurons in layer $B$ act as the logical "AND" operator. The neural output is connected to all output neurons of the classifier through trainable connections. They have weights that are modified during the training stage.

Finally, each neuron in the last layer represents a response from the classifier, and the neuron with the highest excitation value is selected. In this study, we considered two classes, beans and weeds. In future works, the number of classes may be increased to include different types of weeds.

The classifier based on neural networks was selected as it has the advantages of adaptability and robustness.

The RSC neural classifier can be depicted through the following block diagram (Fig.3).

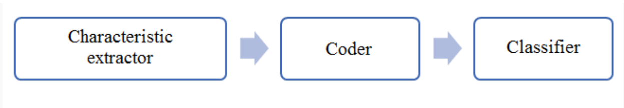


Fig. 3: Block diagram of the RSC classifier

The image characteristics (brightness, contrast, and contour orientations) are calculated in the first block "Characteristic extractor" and are used as the input data for the "Coder" block. Input data corresponds to ($X_1$, $X_2$,…, $X_n$) in Fig.2. The encoder produces a binary vector with a large dimension. This block "Coder" corresponds to blocks 1,,…,$S$ in Fig.2. The vector ($b_1$,…, $b_s$) is the input of the neural classifier. The training process corresponds to changing of weights of connections between penultimate ($B$) and ultimate ($C$) layers in Fig.2 Finally, the output of the neural classifier (maximal excitation of neuron $C_i$) gives us the recognized class (Fig.2).

In general, the process of class recognition is as follows:

• First, the initial structure of the classifier (the masks) is generated, and in this stage the images to be used for training and recognition are selected.

• Subsequently, the coding is generated, and in this stage the images are scanned to obtain the codes of the characteristics, which enter the neural classifier.

• Thereafter, the system training is carried out; during this stage the weights of the connections are modified using the Hebb's rule. If the response is correct nothing must be done. If the answer is incorrect the weights to correct response is necessary to increase and the weights to incorrect response must be decreased. We can present this process with equation (3).

$$\begin{aligned} &\forall k, \quad w_{kr}(t+1) = w_{kr}(t) + a \\ &\forall k, \quad w_{kg}(t+1) = w_{kg}(t) - a \\ &if\left(w_{kg}(t+1) < 0\right) \rightarrow w_{kg}(t+1) = 0 \end{aligned} \qquad (3)$$

where $w_{ki}(t)$ is the weight of the connection between $k$ neuron of the $B$ layer and $i$ neuron of the $C$ layer before training, $w_{ki}(t + 1)$ is the weight of the same connection after training, $a$ is the experimental constant.

• Finally, the system works on recognition by using the images that do not participate in the system's training.

## 3 Experiments

For this task, we collected a base of 20 images of (220 × 220) pixels (examples are presented in Fig.4). Several experiments were carried out, varying the number of images for the training and recognition. It is to be noted that this RSC is a neural classifier with supervised training. Thus, it was necessary to mark the different classes on the images for the training process.

Fig. 4: Images from our database

Each image was pre-processed; it was converted to a grayscale and subsequently, for each image, the pixels in which the bean leaf was found were marked (Fig.5).

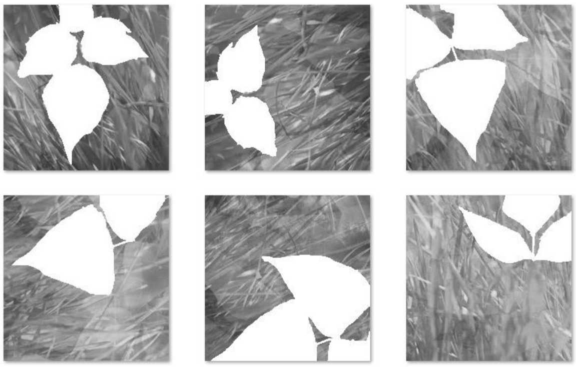

Fig. 5: Marked images

When the marking process was completed, each image was scanned with a window size of (20 × 20) pixels to increase the number of samples to be used by the neural classifier. For each window, the image characteristics were extracted. For this, three types of histograms were calculated: brightness, contrast, and contour orientation histograms. These histograms were used as input for the RSC neuronal classifier.

To calculate the brightness histogram, each pixel of the image was analyzed. To calculate the contrast histogram, two neighboring pixels were analyzed. In this case, the neighboring pixels can be selected horizontally, vertically, or diagonally. We used horizontal pairs of pixels. The difference between the brightness values of two pixels were calculated for the subsequent calculation of the contrast histogram.

For the calculation of the contour orientation histogram, it was necessary to analyze every four pixels of the image. For this purpose, the Schwartz algorithm [21] was used. An example of the obtained histograms is shown in Fig.6.

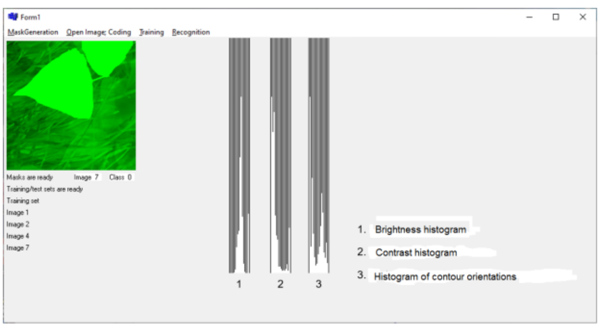


Fig. 6: Extraction of characteristics as histograms

The system functioning started with the scanning of the images to calculate the input parameters of the neural classifier. As mentioned, the images were pre-processed to convert them to a grayscale, and the calculated parameters were the histograms of brightness, contrast, and contour orientation. The system needed to recognize two classes: bean plants and weeds.

After obtaining the input parameters, they were entered into the neural classifier. A (20 × 20) pixel window was used for scanning the images; the step of the window movement was 10 pixels.

After completion of the training procedure, the system worked to recognize the images that did not participate in the training.

The training process changed the weights of the connections between the neurons of the penultimate and ultimate layers of the RSC neural classifier. As mentioned previously, each neuron of the penultimate layer was connected to all the neurons in the ultimate layer. Each of these connections had a weight. During the training process, these connections changed their weights using the Hebb's rule.

If the response of the neural classifier was correct, the weights were not changed. If the answer of the neural classifier was incorrect, the connection weights to the correct class were increased, and those to the incorrect class were decreased. The details of the experiments performed using the RSC neural classifier are presented in Table 1. The main parameters included the total number of images ($M$) and number of images for the training ($M_T$) and recognition processes ($M_R$). Always, $M = M_T + M_R$.

Table 1. Plan of experiments

| Experiment number | Total number of Images ($M$) | Training images number ($M_T$) | Recognition images number ($M_R$) |
|---|---|---|---|
| 1 | 20 | 15 | 5 |
| 2 | 19 | 15 | 4 |
| 3 | 18 | 15 | 3 |
| 4 | 17 | 10 | 7 |
| 5 | 15 | 10 | 5 |
| 6 | 13 | 10 | 3 |
| 7 | 10 | 7 | 3 |
| 8 | 9 | 5 | 4 |
| 9 | 8 | 5 | 3 |
| 10 | 7 | 5 | 2 |

## 4 Results

After performing the experiments, the following results were obtained (Table 2). The first column of the Table 2 corresponds to experiments described in the Table 1. The second column corresponds to recognition rate calculated and presented in percentage.

Table 2. Results

| Number of experiments | Percentage of recognition ($N$ in %) |
|---|---|
| 1 | 96.46 |
| 2 | 95.93 |
| 3 | 97.66 |
| 4 | 88.34 |
| 5 | 78.16 |
| 6 | 76.48 |
| 7 | 85.77 |
| 8 | 72.1 |
| 9 | 65.17 |
| 10 | 70.4 |

How it was calculated? For every window of (20 × 20) pixels input vector was formed and the RSC recognized it. For all images the number of windows that were not correctly recognized (for us it is the number of errors ($M_{err}$)) was calculated. The recognition rate we calculated as:

$$N = \frac{M_R \times (H / h) \times (W / w) - M_{err}}{M_R \times (H / h) \times (W / w)} \times 100\% , \qquad (4)$$

where $N$ is the recognition rate (%); $M_R$ is the total number of images for recognition; $H$ is the image height; $W$ is the image width; $h$ and $w$ are the window size (in our case $h$=$w$=20 pixels).

We were able to obtain favorable results (Table 2) in the experiments. Using 20 images, 15 for training and 5 for recognition, it was possible to obtain a recognition rate of 97.66 %. Using a total of 17 images, 10 for training and 7 for recognition, the recognition percentage decreased to 88.34 %. It is worth mentioning that as the number of total images was reduced, the recognition percentage reduced. For example, when using 5 images for training and 4 for recognition, the recognition percentage was 72.1 %.

These obtained percentages of recognition can be considered as favorable as the image base may not be uniform, that is, each image may contain a different number of bean leaves at different positions and orientations.

As the number of images was increased, the time increased. It is worth mentioning that the recognition time was not long and depended on the image number.

# 5 Conclusion

A significant problem of automatic recognition of bean plants and distinguishing them from weeds was addressed.

An RSC neural classifier was developed and demonstrated to be used for the recognition of the two classes, weeds and bean plants. The results obtained were favorable with a recognition rate of nearly 98 %. This RSC neural classifier can be used in agricultural systems for the recognition of good plants and weeds. Thus, tractors, which can use pesticides, can also protect the crops from weeds in a special and precise manner using computer vision and neural networks.

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## Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Miguel Aparicio, Carlos Vera carried out the simulation and image database

Tetyana Baydyk, Ernst Kussul have implemented the algorithm of RSC neural classifier in C++ (Borland 6)

Graciela Velasco has organized and planned the experiments

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## Conflict of Interest

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