Application of artificial neural networks in image recognition and classification of crop and weeds

C.-C. YANG[1], S.O. PRASHER[1], J.-A. LANDRY[1], H.S. RAMASWAMY[2] and A. DITOMMASO[3]

[1]Department of Agricultural and Biosystems Engineering, McGill University, Ste-Anne-de-Bellevue, QC, Canada H9X 3V9; [2]Department of Food Science and Agricultural Chemistry, McGill University, Ste-Anne-de-Bellevue, QC, Canada H9X 3V9; and [3]Department of Crop and Soil Sciences, Cornell University, Ithaca, NY, USA 14853-2801. *Received 5 May 1999; accepted 30 June 2000.*

Yang, C.-C., Prasher, S.O., Landry, J.-A., Ramaswamy, H.S. and DiTommaso. 2000. **Application of artificial neural networks in image recognition and classification of crop and weeds**. Can. Agric. Eng. **42**:147-152. The objective of this study was to develop a back-propagation artificial neural network (ANN) model that could distinguish young corn plants from weeds. Although only the colour indices associated with image pixels were used as inputs, it was assumed that the ANN model could develop the ability to use other information, such as shapes, implicit in these data. The 756x504 pixel images were taken in the field and were then cropped to 100x100-pixel images depicting only one plant, either a corn plant or weeds. There were 40 images of corn and 40 of weeds. The ability of the ANNs to discriminate weeds from corn was then tested on 20 other images. A total of 80 images of corn plants and weeds were used for training purposes. For some ANNs, the success rate for classifying corn plants was as high as 100%, whereas the highest success rate for weed recognition was 80%. This is considered satisfactory, given the limited amount of training data and the computer hardware limitations. Therefore, it is concluded that an ANN-based weed recognition system can potentially be used in the precision spraying of herbicides in agricultural fields. **Keywords:** artificial neural networks, machine vision, precision farming, weeds, herbicide application, pollution.

L'objectif de l'étude est de développer un modèle qui pourrait distinguer les jeunes plants de maïs des mauvaises herbes. Bien que seul l'indice de couleur calculé à partir d'images numérisées ait été utilisé comme donnée, il a été supposé que le modèle ANN ainsi développé, pourrait être employé pour d'autres types d'informations qui seraient en corrélation directe avec les données premières, comme par exemple la forme. Des images de 756*504 pixels ont été prises dans les parcelles. À partir de celle-ci, d'autres de 100*100 pixels ont été sélectionnées avec comme critère qu'elles ne contiennent qu'un seul plan, soit de maïs, soit de mauvaises herbes. On a pris 40 images de maïs et 40 de mauvaises herbes. La capacité de ANN à distinguer les mauvaises herbes du maïs, a été ainsi testé sur 20 autres images. Un total de 80 images de plants de maïs et de mauvaises herbes a été utilisé pour arriver à nos fins. Pour certains modèles ANN développés, le taux de réussite à reconnaître les plants de maïs, a été aussi haut que 100%. Alors que pour les mauvaises herbes le meilleur résultat n'a atteint que 80%. Ce résultat peut être considéré satisfaisant étant donné les limitations d'une part de l'acquisition de données et d'autre part de la capacité du matériel informatique. En conclusion, un système de détection des mauvaises herbes basé sur ANN peut potentiellement être utilisé dans l'épandage de précision des herbicides dans les champs.

INTRODUCTION

Significant progress in the development of machine vision and image processing technology has been made in the past few years in conjunction with improvements in computer technology (Baxes 1994). Equipment for machine vision and image processing has been reduced in cost, size, and weight, can be installed in most vehicles (e.g., tractors), and is accessible for civilian use. Machine vision and image processing are used increasingly in biology, materials science, photography, and other fields (Baxes 1994). Many experiments have suggested that machine vision can be used to recognize and localize weeds in agricultural fields (Anonymous 1994a, 1994b; Blackmer and Schepers 1996; Meyer et al. 1997; Schmoldt et al. 1997; Staff and Benlloch 1997). It might therefore be used to control site-specific spraying herbicide application, thus reducing both environmental pollution from the overuse of agrochemicals, as well as the cost of weed control.

It is presently quite difficult to use machine vision to distinguish weeds from the main crop in real time, due to the substantial computational resources and the complicated algorithms required. Artificial neural networks (ANNs) can overcome some of these difficulties by interpreting images quickly and effectively. ANNs are composed of numerous processing elements (PEs) arranged in various layers, with interconnections between pairs of PEs (Haykin 1994; Kartalopoulos 1996; Kasabov 1996). They are designed to emulate the structure of natural neural networks such as those of a human brain. For most ANNs, PEs in each layer are fully connected with PEs in the adjacent layer or layers, but are not connected to other PEs in the same layer. The PEs simulate the function of the neurons in natural neural networks, while the interconnections between them mimic the functions of dendrites and axons.

There have been many applications of ANNs reported for the interpretation of images in the agri-food industry. Studies have shown that for the interpretation of images ANNs can be as accurate as procedural models (Deck et al. 1995; Timmermans and Hulzebosch 1996). For example, the accuracy of classification of potted plants can be greater than 99% (Timmermans and Hulzebosch 1996), apples can be graded by colour with an accuracy of 95% (Nakano 1997), the classification of logs for defects using computed tomography imagery can be 95% accurate (Schmoldt et al. 1997), and the accuracy for the classification of wheat kernels by colour can be 98% or more (Wang et al. 1999). Generally, ANNs can efficiently model various input/output relationships with the advantage of requiring less execution time than a procedural model (Yang et al. 1997a, 1997b). These features make the ANN approach very appealing for real-time image processing.

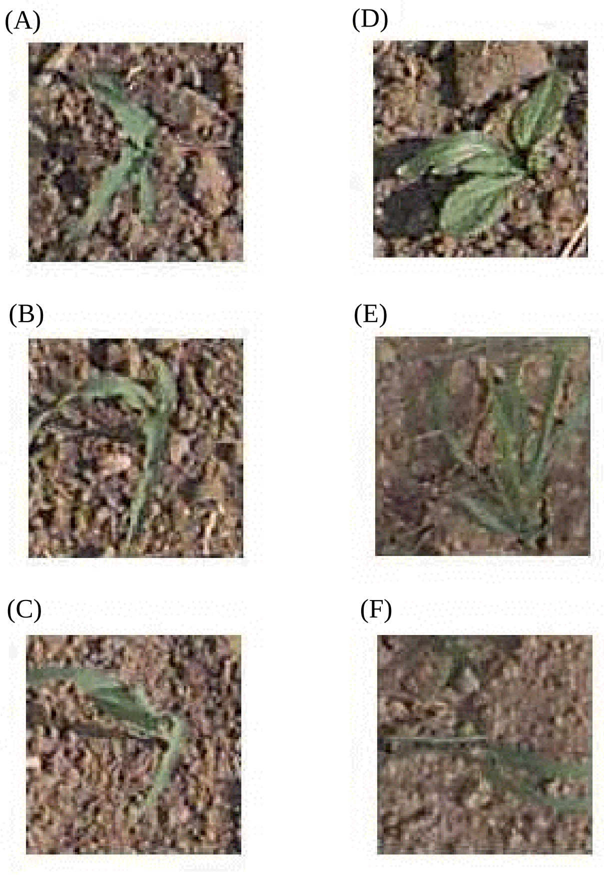

Fig. 1. Examples of 100x100 cropped images. (A) and (B) for corn in training data set; (C) for corn in test data set; (D) and (E) for weeds in training data set; and (F) for weeds in test data set.

Given the aforementioned considerations, it was decided to use ANNs for weed recognition in this study. Specifically, the possibility of using ANNs to distinguish between images of crop plants and weeds, captured in real-time by a digital camera, was investigated. In this study, the use of ANNs was confined to the differentiation of corn (*Zea mays*, L.) and seven weed species commonly encountered in the experimental fields.

MATERIALS and METHODS

A Kodak DC50 zoom camera was used to acquire digital images of corn plants and weeds in two experimental fields (#18 and #24) on the Macdonald Campus Farm of McGill University, Ste-Anne-de-Bellevue, QC, Canada, in 1997. Images were taken from Field #18 on June 11, 12, and 20 and from Field #24 on June 10, 13, and 20, the time at which post-emergent herbicide application is usually carried out. The pictures were taken at several randomly-chosen locations in the fields. During image collection, the camera was always held at the same height (600 mm) to capture a bird's-eye view of objects on the ground. Since the size of the plants varied significantly from one spot to another, it was necessary to zoom in or out to obtain clear images. Although the actual area covered varied slightly from image to image, it was approximately 300 mm x 200 mm.

The most common weeds in the fields were *Agropyron repens*, *Cyperus esculentus*, *Plantago major*, *Stellaria media*, *Chenopodium album*, *Abutilon theophrasti* and *Taraxacum officinale*. Together, these weed species constituted one category of objects to be differentiated from corn plants. To simplify the experiment, the study did not involve the training of ANNs to distinguish between different species of weeds. The differentiation between various weed species will be carried out in a future study.

The digital images were downloaded to a personal computer having a Pentium 200MMX microprocessor and 96 MB of RAM and were converted from the native Kodak digital camera format (KDC) to the 8-bit colour bitmap format (BMP). The size of the images was 756x504 pixels. These images were viewed and further cropped to a size of 100x100 pixels so that each included either a corn plant or a group of weeds. It would have been impractical to use the 756x504 pixel images, since the PC memory would have been inadequate. Care was taken not to include both corn and weeds in a given image, so as to simplify the ANN training process. Mixed images, containing both corn plants and weeds, will be used in future studies. Some examples of cropped images are shown in Fig. 1.

After the BMP images were obtained, they were pre-processed with the Image Processing Toolbox v2.0 for MATLAB v5.0 (MathWorks 1997a, 1997c). The BMP images were converted to indexed images based on a red-green-blue (RGB) colour system. Each pixel of an image was classified into one of 256 categories, represented by an integer in the range from 0 (black) to 255 (white). Each assigned colour index number served as an ANN input and, therefore, there were 10 000 (100x100) inputs for each image. Although the colour indices were the only inputs used in this study, other features, such as shapes, were expected to be taken into account by the ANNs since information about them is implicit in the relationships between the pixel colours.

The Neural Network Toolbox v2.0 for MATLAB v5.0 (MathWorks 1997b, 1997c) was used to build the ANN models. During training, the ANNs were presented with binary output data. Two classification schemes were tried to represent the output data. In one scheme (Type 1), as shown in Fig. 2, there was only one output variable in the training data set. An output variable value of zero was assigned to weeds and a value of one to corn. In the other scheme (Type 2), as shown in Fig. 3, there were two output variables; the first was an estimate of the possibility that the object was a corn plant, and the second was an estimate of the possibility that it was a weed. For a corn plant, the first output should be one and the second should be zero, and vice-versa for a weed. Forty images of corn and forty images of weeds were used to train the ANNs. Testing was done with 10 other images of corn and 10 of weeds.

While crisp values of one and zero were used during training, values between zero and one could result during the testing of the ANNs, and some strategy was therefore required to deal with such values. To address the problem of uncertain classification, two schemes were tested for the Type 1 classification and four were tested for the Type 2 classification. These are named Type 1-A and Type 1-B, and Type 2-A to Type 2-D. The conditions under which an object was recognized as a weed or a corn plant are summarized in Table I. Both output methods would ideally lead to the same results if the

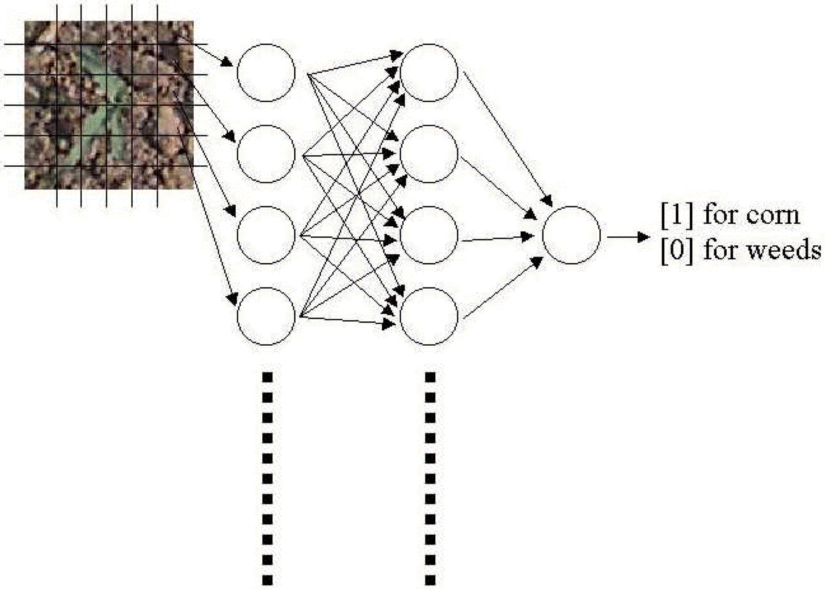

Fig. 2. The ANN structure for Type 1 output.

same classification thresholds are used and if there are enough images to ensure proper training of the ANNs. However, the slightly different ANN architectures that are used in each method could lead to differences in effectiveness, and, moreover, the Type 2 method allows a more flexible interpretation of the results.

Various types of ANNs can be created with MATLAB. Back-propagation networks were selected for this project because they have been successfully used in various image processing applications in agriculture (Deck et al. 1995; Schmoldt et al. 1997; Timmermans and Hulzebosch 1996; Wang et al. 1999). Each PE in the input layer received the colour index value of one of the pixels in the input images. One hidden layer was used between the input and output layers. Due to the choice of the back-propagation network, the input data was normalized so that it ranged from zero to one (instead of from zero to 255) before being presented to the ANN. A log sigmoid transfer function was implemented in each PE.

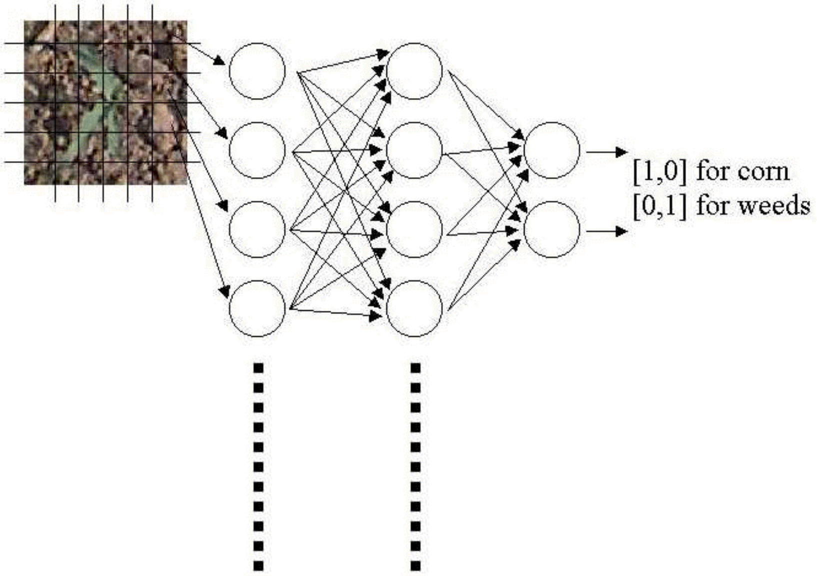

Fig. 3. The ANN structure for Type 2 output.

During the training procedure of the ANNs, the maximum acceptable sum-squared error was empirically set at $1x10^{-5}$. The training process was carried out with fast back-propagation, until a maximum of 2000 epochs (cycles) or the maximum acceptable sum-squared error was reached. Some initial runs showed that these settings appeared to be sufficient for this study.

A trial-and-error method was used to set the number of PEs in the hidden layer. For the Type 1 output, the number of PEs in the hidden layer was arbitrarily selected and varied from 70 to 300. For the Type 2 output, the number of PEs in the hidden layer was varied from 120 to 300. Computer memory in this study was insufficient for training an ANN with more than 300 PEs in the hidden layer. The success classification rate for each object (corn or weeds) was determined after training in order to evaluate the ANN model performance.

The McNemar test for the significance of changes (Daniel 1990; Fleiss 1981) was used to compare each pair of output types for the ANNs with the same number of PEs in the hidden layer. It is a chi-square test based on the binomial distribution for matched pairs of data. The critical value of the test statistic was chosen to be 1.96 (signifying a confidence level of 95%). When the computed value of the test statistic is less than 1.96, two output types compared by the McNemar test are not significantly different. In addition, the Brier score (Hand 1994) was used to evaluate the predictive ability of different ANN models containing different numbers of PEs. It is a unitless index of predictive accuracy and the range of the Brier score is from zero to one. The smaller the score is, the better is the predictive ability of the model.

RESULTS and DISCUSSION

The ANN's ability to properly classify images using the Type 1 output and the two evaluation schemes is shown in Table II for various numbers of PEs in the hidden layer. As shown in Table II, the Brier scores varied from 0.153 to 0.271. The lowest Brier score was obtained by the ANN with 110 PEs in the hidden layer. The generally low Brier scores indicate the potential capability of ANNs to classify and recognize images. However, the ANN model with the lowest Brier score does not necessarily mean the best model in this case since it is not expected for a model that would give the best prediction efficiency for both corn and weed image recognitions. Rather, it is very important for our application that weed images do not get classified as corn since it would lead to poor weed control and yield losses. Thus, it is necessary to further analyse the ANN model performance in detail and carefully consider the success recognition rates for classifying corn and weeds.

Table I. The output types of ANNs and the threshold of classification.

Type	Corn	Weeds
1-A	Output > 0.5	When the output did not match the condition in the left column.
1-B	Output > Average value of all outputs	
2-A	When the output did not match the condition in the right column.	Second output > First output
2-B		(Second output > First output) or (Second output > 0.5)
2-C		(Second output > First output) or (Second output > Average value of first outputs)
2-D		Second output > 0.5

Table II. Success classification rate for Type 1 ANNs.

PEs in the hidden layer	Brier Score	Type 1-A		Type 1-B	
		Corn (%)	Weeds (%)	Corn (%)	Weeds (%)
70	0.23	80	60	70	70
80	0.17	90	60	80	70
90	0.23	80	40	60	80
100	0.17	80	80	70	80
110	0.15	100	60	80	70
120	0.19	80	50	70	80
130	0.21	70	70	60	70
140	0.25	60	50	60	70
150	0.20	90	60	70	60
160	0.27	80	50	80	50
180	0.19	90	60	90	70
200	0.24	90	40	90	50
220	0.21	90	60	90	70
230	0.17	90	60	90	70
240	0.24	90	50	90	60
260	0.22	90	50	80	60
280	0.21	90	60	80	60
300	0.19	90	70	90	70

The results shown in Table II indicate that ANNs can, in general, classify and distinguish images of corn plants from images of weeds with a success rate of 80 to 100%. The success rate for distinguishing images of weeds from images of corn plants often lay between 70 to 80%, although sometimes it was as low as 50%. Results indicate that, after training, ANNs seemed to misclassify more weed images as images of corn plants than vice versa, i.e., the success recognition rate for corn is always higher than the success recognition rate for weeds. When the threshold value for classification was set at 0.50 (Type 1-A), indicating an equal possibility of either corn or weeds, the success rate for recognizing corn was 100%, which was much higher than the corresponding success rate for recognizing weeds (60%). The lower success rate for weed detection indicates it is more likely for an ANN to misclassify weeds as corn. In the real world, this situation is highly undesirable and it could lead to inadequate herbicide application and weed control.

To reduce the possibility of missing weeds, the threshold was set at the average value of 20 outputs, 0.62, for Type 1-B output, meaning that when images are difficult to classify, more images would be classified as weeds. In some cases, the success recognition rate for weed classification with this scheme was increased by 10% (i.e., for an ANN with 220 PEs in the hidden layer) to 40% (i.e., for an ANN with 90 PEs in the hidden layer). At the same time, however, the success recognition rate for corn classification decreased by 10% (i.e., for an ANN with 100 PEs in the hidden layer) to 20% (i.e., for an ANN with 90 PEs in the hidden layer).

To compare and evaluate the two Type 1 output schemes, the McNemar test was used to perform pairwise comparisons. Although the results from Type 1-A and Type 1-B appear to be different (Table II), the results of the test in Table III show that the difference between these two output schemes is not significant ($P \leq 0.05$).

As shown in Table II, single-output ANNs did not accurately classify some images. The actual values of ANNs outputs for these images were around 0.50 or 0.62, instead of approaching zero or one. To attempt to improve this situation, additional ANN models were created that produced two outputs. The first output represented the possibility of the image being of a corn plant while the second output represented the possibility of it being of a weed. Four schemes for this type of classification were investigated in this study. Due to a greater number of PEs in the output layer, no ANNs were investigated that had less than 120 PEs in the hidden layer. The Brier scores and the success recognition rates for the four Type 2 schemes are given in Table IV. Some of the comparisons by the McNemar test between the Type 1-A and each of the Type 2 are also presented in Table III.

The Brier scores in Table IV range from 0.241 to 0.358. The lowest Brier score was obtained by an ANN with 160 PEs in the hidden layer. Although this model is among the best for corn recognition, the success recognition rate for weeds is unsatisfactory. As stated earlier, this is contrary to the results expected in this study since weed misrecognition would lead to poor weed control and significant yield losses. Therefore, it also requires further analysis and interpretation of the results.

Generally, the success classification rates shown in Table IV ranges from 60 to 90% for corn and from 40 to 80% for weeds.

Table III. Some results of the McNemar test between different outout types of ANNs.

PEs in the hidden layer	Type 1-A vs Type 1-B	Type 1-A vs Type 2-A	Type 1-A vs Type 2-B	Type 1-A vs Type 2-C	Type 1-A vs Type 2-D
120	1.732	1.000	0.447	1.000	0.447
140	1.000	1.342	1.342	1.342	1.342
160	0.000	1.000	1.000	1.000	1.000
180	1.000	0.000	0.000	0.000	0.000
200	1.000	1.000	1.000	1.000	1.000
220	1.000	1.414	1.414	1.414	1.414
240	1.000	0.000	1.000	1.000	1.000
260	0.000	0.447	0.000	0.447	0.447
280	0.000	0.577	0.577	0.577	0.577
300	0.000	0.000	0.000	0.000	0.000

Comparing Tables II and IV, the success classification rate for weeds is greater in some cases for the Type 2 method. For example, an ANN with 200 PEs in the hidden layer had a success recognition rate for weeds increased from 40 to 50% (Table II) to 70 to 80% (Table IV). An ANN with 260 PEs in the hidden layer had a success recognition rate for weeds that increased from 50 to 60% (Table II) to 70 to 80% (Table IV). The success rate of corn classification, however, decreased in all these cases. Such a dilemma was also observed with results obtained using the Type 2-A to 2-D schemes. For the same number of PEs in the hidden layer, the highest success rate for weed classification was obtained using the Type 2-C scheme. However, the success rate for corn recognition was generally lower with the Type 2-C scheme than the others. With the Type 2-C scheme, only the ANN with 200 PEs in the hidden layer could obtain the success recognition rates as high as 80% for both corn and weeds.

Although ANNs using different Type 2 analysis schemes differed from one another in performance, as shown in Table III, the McNemar test indicated that these differences were not statistically significant ($P \leq 0.05$). Neither did the McNemar test show any significant differences between the results of the Type 1 and Type 2 methods. However, particular analysis schemes might still be better-suited to certain image classification and recognition problems since they do provide different ways of looking at the output.

To further improve ANN performance in image recognition and classification, other methods may be investigated in the future. Firstly, due to computer memory limitations, the number of PEs in the hidden layer was limited to 300 in this study, i.e., 3% of the number of input PEs. Although there is no method for determining the best number of PEs to include in the hidden layer based on the number of inputs, the number of PEs used in this work may have been insufficient for such a large amount of input data. More PEs in the hidden layer would result in better performance. However, more computer memory would be required to generate such ANNs, and a faster processor would also be needed to save time during training. Secondly, the training data set contained only 80 images, which might not have been sufficient. It would be necessary to collect more data from the field to increase the size of the training data

Table IV. Success classification rate for Type 2 ANNs.

PEs in the hidden layer	Brier Score	Type 2-A		Type 2-B		Type 2-C		Type 2-D	
		Corn (%)	Weeds (%)	Corn (%)	Weeds (%)	Corn (%)	Weeds (%)	Corn (%)	Weeds (%)
120	0.270	90	50	80	50	80	60	80	50
140	0.245	90	50	90	50	90	50	90	50
160	0.241	90	50	90	50	90	50	90	40
180	0.250	90	60	90	60	90	60	90	60
200	0.325	80	70	80	70	80	80	80	70
220	0.305	80	50	80	50	70	60	80	50
240	0.257	90	50	90	60	90	70	90	60
260	0.358	60	70	60	80	60	80	70	80
280	0.305	80	60	80	60	80	60	80	60
300	0.301	90	70	90	70	80	70	90	70

set and ensure proper training. Although the results in this study do not show statistically significant differences among the various output analysis methods used, by the McNemar test, the notable results, that were observed, point to a need to further investigate different methods for image classification using ANNs. To generally evaluate the ANN performance by different numbers of PEs in the hidden layer, the Brier score can be used. To investigate the detail of ANN performance for corn or weed recognition, the success recognition rate for each plant object should be discussed respectively. The McNemar test can be used to examine the differences between different ANN methods.

Another noteworthy result from this study is that while the time needed to train an ANN model was approximately 20 hours, the testing time was usually less than one second per image. This information is of paramount importance for real-time weed recognition and herbicide application problems where one may have only a few seconds to do the recognition and communicate with the controller of the herbicide sprayer to make informed decisions about site-specific spraying.

SUMMARY

This study was undertaken to develop an ANN to classify images taken from the field and detect the presence of weeds. The images were taken from cornfields in Ste-Anne-de-Bellevue, southwestern Québec, Canada, in June 1997. Colour index values were assigned to the pixels of the indexed image and used as ANN inputs. There were 80 images, 100x100 pixels, for training, and 20 images for testing. Many back-propagation ANN models were developed with different numbers of PEs in their hidden and various output layers. Six different evaluation schemes for two ANN output strategies were used. The performance of the ANNs was compared and the success rate for the identification of corn was observed to be as high as 80 to 100%, while the success rate for weed classification was as high as 60 to 80%. The Brier score and the McNemar test were used to statistically evaluate the results obtained in this study. Although the study was limited by the available computational resources and training data, the results indicate the potential of ANNs for fast image recognition and classification. Fast image recognition and classification can be useful in the control of real-world, site-specific herbicide application. Challenges still remain, however, in the analysis of real-world images where corn, weeds, and other plants may appear together.

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