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A hybrid artificial neural network–bee colony algorithm for machine vision-based weed detection in potato fields

Nadia Saadati[1*], Ali Najar[2]

[1] *Department of Agricultural Biosystems Engineering, University of Mohaghegh Ardabili, Ardabil, Iran*
[2] *Department of Computer Engineering, Sharif University of Technology, Tehran, Iran*

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*** Corresponding author**
nadia.saadati@uma.ac.ir

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ABSTRACT

With advancements in technology, particularly in electrical and mechanical engineering, the agricultural sector is increasingly looking to adopt such technologies. One of the areas of interest for researchers is the use of modern technologies to optimize herbicide spraying in agricultural fields. Manual removal of weeds and the use of herbicides are time-consuming and costly, and cause more resistance in weeds. It also has many consequences for the environment and humans. As a result, it is necessary to use herbicides optimally and appropriately. One possible solution is the use of machine vision systems. In this study, we developed a video-based machine vision system designed to identify two common weeds found in potato fields: white goosefoot (*Chenopodium album*) and knotweed (*Polygonum aviculare*). After video recording, preprocessing, and segmentation, 1688 individual objects were detected. Four key features extracted from images, including the third moment invariant, perimeter, fifth moment invariant, and sum entropy, were considered inputs to classify weed type using a hybrid model based on artificial neural networks optimized by a bee colony algorithm. To evaluate the classifier's performance, sensitivity, precision, specificity, F1-score, accuracy, and false positive rate were calculated. For test data, the sensitivity of the classification of white goosefoot and knotweed was 97% and 89%, respectively. The overall precision was close to 94%, while the specificity of the classification of white goosefoot and knotweed was 89% and 97%, respectively.

1. Introduction

Real-time weed detection is a significant challenge in precision agriculture since weed growth is considered one of the most challenging problems in agriculture (Delmotte et al., 2011; Shennan et al., 2017). This challenge arises from two primary factors: first, the natural variability among weeds, which can differ in leaf shape, size, and texture; and second, the interdisciplinary knowledge required, as researchers in weed detection need skills in both agriculture and technical fields such as computer programming. Some researchers have focused on distinguishing between broadleaf and narrow-leaf weeds.

The most common method for weed control is the use of herbicides, which have shown significant environmental concerns and negative effects on human health and the planet (Ghazali et al., 2008; Zahm and Ward, 1998). Additionally, resistance to herbicides has been observed among specific populations of weeds, which is a cause for concern (Chitra et al., 2006; Wilson, 2000). Meanwhile, weed management in agricultural crops has been a challenging task, and if done promptly, it can prevent up to 34% of yield loss (Oerke, 2006; Zwerger et al., 2004; Liakos et al., 2018; Jiebman et al., 2016). Therefore, selecting a fast, accurate, and non-destructive method is of high importance. To address this issue, Hlaing and Khaing (2014) emphasized the economic significance of classifying weeds and crops in agriculture. They analyzed rape plants and three types of weeds—Lanchon, Amaranth, and Kyaut kut—using 35 images taken at a 45-degree angle and 15.2 cm height above the ground in natural light. Their proposed algorithm involved five main stages: preprocessing, binarization, segmentation, grayscale conversion, and area-based classification, achieving an accuracy of 82.85%.

Dadashzadeh et al. (2020) conducted studies on the identification of rice plants and two types of rice weeds using a bee colony algorithm. The overall accuracy in their research ranged from 76.62% to 92.02%. Another study focused on identifying radishes and weeds using a type of machine vision system. In this research, the identification rate for radishes was 92%, and for weeds, it was 98%, with optimized results using artificial neural networks (ANNs) reaching 100% (Cho et al., 2002). Additionally, a machine vision system was used in a sugar beet field to distinguish between plant leaves and weeds. In this study, ANNs and support vector machines (SVMs) were employed for identification, achieving accuracies of 92.92% and 95%, respectively. The results indicated that the SVM method had better capabilities in identifying weeds, successfully detecting four types of weeds (Bakhshipour and Jafari, 2018). Another successful study in this area used two methods, Back-propagation neural network (BPNN) and SVM, for identifying soybean weeds. The accuracy of the BPNN method was 95.078%, and the SVM method achieved 96.601%, indicating the project's success (Abouzahir et al., 2018). The bee colony algorithm was also used in another study for identifying two types of weeds due to its effectiveness in weed-related research. This model

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achieved prediction accuracy ranging from 67-95% for plants and 84-99% for weeds (Shah et al., 2021). A more comprehensive study was conducted on weed identification using a machine vision system. In this paper, over 1,000 images were taken for each of the five common weed species, i.e., Ambrosia, Amaranthus, Bindweed, Bromus, and Quinoa, in various geographical areas in Kazakhstan. This research utilized classic machine learning algorithms such as K-nearest neighbors, random forest, and decision tree, achieving accuracies of approximately 83.3%, 87.5%, and 80%, respectively (Urmashev et al., 2021). A similar study was also conducted, which collected a comprehensive dataset of four different crops and two types of weeds (Para grass and Nutsedge) for the weed detection system and evaluated the performance of various machine learning classifiers for weed detection using the OpenCV and Keras libraries in Python (Sarvini et al., 2019).

This study aims to detect white goosefoot (*Chenopodium album*) and knotweed (*Polygonum aviculare*) as important weeds in potato fields using video processing and a hybrid ANN and bee colony algorithm classifier. The results of this study can be applied in precision agriculture, allowing for site-specific spraying in potato fields.

2. Materials and Methods

2.1. Video recording

The study was conducted in a 4-ha potato field in Kermanshah Province, planted with Agria potatoes. Videos were recorded with a digital camera (WB151F CCD, 14.2 MP, 30f/s, Samsung, Korea) positioned 40 cm above the ground. The recordings were made in a controlled setting using a filming enclosure covered with tarpaulin, with white LED lights at an intensity of 327 lux to capture the natural color of the plants. The target weeds were goosefoot and knotweed.

2.2. Image segmentation process

To develop and test the proposed machine vision system, an 80-s video database was created (including 56 s for training and 24 s for testing). After video recording, frames were extracted from the video for preprocessing and feature extraction. The first step was segmenting objects, i.e., connected pixels in a frame, from the background (soil, straw, etc.). After examining several color spaces, including RGB, CMY, HSV, and YCbCr, the RGB color space was selected. Based on a trial and error method, Eq. (1) was used to separate objects from the background for each pixel (i,j), retaining pixels where the green (G) component was greater than the red (R) or blue (B) components (Gonzalez et al., 20024).

$$R(i,j) \leq G(i,j) \ | \ B(i,j) \leq G(i,j) \tag{1}$$

2.3. Feature extraction

Various feature domains were used, including texture features based on gray-level co-occurrence matrices (contrast, correlation, sum entropy, and entropy difference), moment invariants (fourth and fifth moments), and shape features (area, perimeter, elongation, and compactness). These features capture differences in texture, leaf orientation, and shape.

2.4. Effective feature selection

Due to the time constraints in real-time spraying, the number of features chosen for classification should be minimized. Some features may overlap, making it unnecessary to use all of them. Therefore, effective features were selected using a hybrid ANN and simulated annealing algorithm. Out of 13 extracted features, the third moment invariant, perimeter, fifth moment invariant, and sum entropy were selected.

2.5. Classification

In this study, we used a hybrid classifier combining an ANN and a bee colony algorithm. Unlike statistical classifiers, this classifier does not require prior assumptions and can handle missing or contradictory data based on general patterns in the rest of the data.

2.6. Performance evaluation metrics

Performance evaluation metrics are essential for assessing the performance of classification models and ensuring their suitability for practical applications. Metrics such as precision, recall, F1-score, specificity, accuracy, and false positive rate provide a comprehensive framework for evaluating different aspects of model performance. These metrics collectively enable a detailed analysis of the classifier's effectiveness, offering valuable insights into its strengths and limitations (Wisang, 2013; Sabzi and Abbaspour-Gilandeh, 2018; Sabzi et al., 2017; Correa et al., 2009; Sabzi et al., 2019). Precision (Eq. 2) measures the proportion of true positive predictions out of all positive predictions made by the classifier.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Recall (Sensitivity) (Eq. 3) indicates the proportion of actual positive instances that were correctly identified by the classifier.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

F1-score (Eq. 4) is the harmonic mean of precision and recall, providing a single metric that balances both.

$$\text{F1} - \text{score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

Specificity (Eq. 5) measures the proportion of actual negative instances correctly identified by the classifier.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{5}$$

Accuracy (Eq. 6) represents the overall correctness of the classifier, calculated as the proportion of correct predictions out of total predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

False Positive Rate (FPR) (Eq. 7) indicates the proportion of actual negative instances incorrectly classified as positive.

$$\text{FPR} = \frac{FP}{FP + TN} \tag{7}$$

3. Results and Discussion

The confusion matrix provides information on the number of correctly classified data points as well as the number misclassified in other classes (Liu et al., 2015). Figure 1 shows the classification results for the test data. Out of 554 samples of goosefoot, only 20 were mistakenly classified as knotweed, while out of 169 knotweed samples, 15 were misclassified as goosefoot. Table 1 presents the sensitivity, precision, specificity, F1-score, accuracy, and false positive rate for each class. A sensitivity of above 90% indicates that the classifier correctly identifies all samples in the target class, and a specificity of above 90% indicates no false-positive classifications in a particular class.

Figure 2 shows the ROC curve for the hybrid ANN-bee colony algorithm classifier in the test phase. A larger area under the curve indicates better classifier performance. The closer the curve is to vertical, the better the classifier performs (Guijarro et al., 2015). As seen, the curves approach vertical, suggesting high classifier performance.

4. Conclusion

The findings of this study demonstrate the potential of a hybrid ANN and bee colony algorithm in developing a robust machine vision system for weed detection in precision agriculture. The use of the RGB color space under controlled lighting conditions proved effective for segmentation tasks, enabling accurate separation of plant objects from the background.

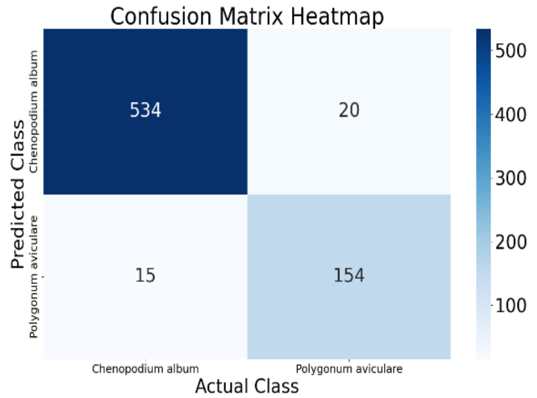

Figure 1. Test data classification using the hybrid neural network - bee algorithm classifier

Table 1. Performance metrics for the two classes

Class	Precision	Recall	F1-Score	Specificity	Accuracy	FPR
Goosefoot	0.96	0.97	0.97	0.89	0.95	0.11
Knotweed	0.91	0.89	0.90	0.97	0.95	0.03

However, challenges remain when dealing with plants that share similar features, as this can reduce classifier accuracy and require further refinement in feature selection and classification strategies. Major field limitations in designing a site-specific spraying machine vision system include varying ridge height, row spacing, ridge width, and potato planting precision. Key limitations related to field applications include varying ridge heights, inconsistent row spacing, differing ridge widths, and the accuracy of potato planting, all of which can impact the effectiveness of site-specific spraying systems.

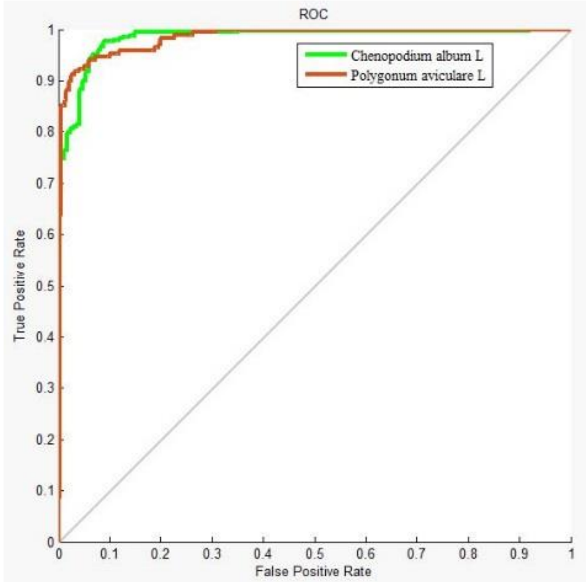

Figure 2. The ROC curve during the testing phase for the hybrid ANN-bee colony algorithm classifier

The classifier demonstrated promising performance, with sensitivity for test data at 97% for goosefoot and 89% for knotweed, alongside high specificity. These results indicate its potential for practical application in site-specific herbicide spraying. Future work could focus on integrating this system into autonomous agricultural machinery and optimizing real-time performance, paving the way for enhanced precision agriculture practices with reduced environmental impact and herbicide usage.

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