

Spectral discrimination of crops and weeds using deep learning assisted by wavelet transform and statistical preprocessing

Research Article

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Abstract

Automatic detection and removal of weeds is a challenging task that requires precise sensors. While crops and weeds possess similar features in terms of appearance, they can be discriminated based on spectral information. This can be done because any object has its own specific spectral signature based on its physical structure and chemical contents. This study examined the use of wavelet transform and deep learning for discrimination of weeds from crops. A total of 626 spectral reflectances in the range of 380 to 1,000 nm were obtained for three crops (cucumber [*Cucumis sativus* L.], tomato [*Solanum lycopersicum* L.], and bell pepper [*Capsicum annuum* L.]) and five different weeds (bindweed [*Convolvulus* spp.], purple nutsedge [*Cyperus rotundus* L.], narrowleaf plantain [*Plantago lanceolata* L.], common cinquefoil [*Potentilla simplex* Michx.], and garden sorrel [*Rumex acetosa* L.]). Morse wavelet was employed to decompose the spectra and extract the scalograms, which are the RGB representations of the spectral data. Two deep convolutional neural networks (i.e., GoogLeNet and SqueezeNet) were employed for the recognition of crops and weeds. In addition, six common classifiers, including linear discriminant analysis, quadratic discriminant analysis, linear support vector machine, quadratic support vector machine, artificial neural networks, and k-nearest neighbors classifier (KNN), were used for the task of crop/weed discrimination to build the comparison with the proposed method. The error of prediction gradually decreased, and a 100% correct classification was achieved after 258 iterations. Analysis showed that SqueezeNet provided classification of 100% accuracy, while GoogLeNet's accuracy was 97.8% for the test set. Among the common classifiers, KNN provided the highest accuracy (i.e., 100%). This study showed that the proposed method can be successfully utilized for classification of crops and weeds.

Introduction

Weeds, which are considered to be any unwanted plants in the field, not only affect the crops around them, but can also jeopardize agricultural areas. Weeds compete for nutrients, soil, water, and space and should be detected and eliminated at an early stage. As the most important crop protection strategy, weed control can lead to a 20% increase in yield (Buddenhagen et al. 2020). Traditional weed control using chemicals is expensive and can be reduced by more than 50% if novel technologies are employed (Gerhards et al. 2022). The use of herbicides has environmental impacts, including potentially polluting soil, surface water, and groundwater (Agüera-Vega et al. 2021; Akbarzadeh et al. 2018; Le et al. 2019; Sabzi and Abbaspour-Gilandeh 2018; Slaven et al. 2023; Sunil et al. 2022). However, weed detection and control constitute a complicated affair, as crops and weeds are quite similar in many aspects, including color features, leaf shapes and forms, leaf patterns, and leaf/plant dimensions (Iqbal et al. 2020; Liu et al. 2019; Sodjinou et al. 2021). Recently, weed detection and separation from crops have advanced rapidly and have benefited from modern solutions. These recent solutions include satellite-based detection (Rasmussen et al. 2021; Shanmugam et al. 2020; Shendryk et al. 2020), drone-based detection (Esposito et al. 2021; Liang et al. 2019; Revanasiddappa et al. 2020), hyperspectral imaging (Che'Ya et al. 2021; Li et al. 2021; Pignatti et al. 2019; Sulaiman et al. 2022), and multispectral imaging (Barrero and Perdomo 2018; Osorio et al. 2020).

Spectral detection can be a promising solution for crop/weed separation based on the concept that every object in the nature has its own spectral signature (Falcioni et al. 2020; Putra 2020). This spectral signature comes from the physical properties and the nutrient, chemical, and water contents. These properties influence the amount of absorption and reflection of electromagnetic

waves that can be used for distinguishing crops and weeds. The use of spectral data in agricultural applications has been extensively researched. Applications include crop/weed discrimination (Fletcher et al. 2016; Gómez-Casero et al. 2010; Kamath et al. 2020; Subeesh et al. 2022), disease detection (Cordon et al. 2021; Mahlein et al. 2010, 2013; Shafri et al. 2011), ripeness estimation (Silalahi et al. 2016), estimation of plant nutrient deficiencies (Abdulridha et al. 2018; Ayala-Silva and Beyl 2005), classification of grass-dominated habitats (Bradter et al. 2020), plant species/varieties discrimination (Manevski et al. 2011; Prospere et al. 2014; Ullah et al. 2012; Vaiphasa et al. 2007; Yu et al. 2020), distinguishing herbicide-resistant plants (Jones et al. 2023), and classifying forest logging residue (Acquah et al. 2016). In all these applications, the discrimination or detection technique was built using the specific spectral reflection of plants or plant organs. There has been one or several wavelengths in which the reflectance of electromagnetic energy has been different for the healthy crop and weed, diseased crop, or malnourished crop. In this regard, the use of hyperspectral data analysis can provide promising tools that are fast and generalizable and can be integrated in the analyses with semi-automated procedures (Hennessy et al. 2020). Another advantage of spectral datasets is the potential for detailed analysis of spectral reflectance which comes from biochemical and biophysical attributes of plants. However, a disadvantage of hyperspectral analysis is the processing of the data, which can be difficult due to the high dimensionality of the data. Also, the excessive demand for obtaining and providing sufficient samples and the high cost of spectral measurements are among the limitations of hyperspectral technologies (Adelabu et al. 2013). While spectral data have been quite critical for species discrimination, a disadvantage is the redundant information within high-resolution spectral data (Nagasubramanian et al. 2019).

Among the techniques that mostly have been used for the analysis of spectral data and classifications are k-nearest neighbors classifier (KNN), linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), principal component analysis, Normalized Difference Vegetation Index (NDVI), Fourier transform, Jeffries–Matusita distance measure, support vector machines (SVMs), and artificial neural networks (ANNs) (Bell and Baranoski 2004; Durgante et al. 2013; Longchamps et al. 2010; Louargant et al. 2018; Noble and Brown 2009; Strothmann et al. 2017; Talaviya et al. 2020; Zarco-Tejada et al. 2018). Symonds et al. (2015) developed a real-time plant discrimination system based on discrete reflectance spectroscopy. In this study, three different laser diodes (i.e., 635, 685, and 785 nm) were used. It was reported that the system could make a practical discrimination for a vehicle speed of 3 km h⁻¹. In a recent work, Nidamanuri (2020) used machine learning to discriminate tea (*Camellia sinensis* (L.) Kuntze) plant varieties. Canopy-level hyperspectral reflectance measurements were acquired for tea and natural plant species in the range of 350 to 2,500 nm. The classifier could discriminate six out of nine tea plant varieties successfully, with accuracies between 75% and 80%.

Recently, attention has been paid to the implementation and improvement of convolutional neural networks (CNNs) for classification purposes. The good thing about CNNs is that they learn features on their own through the network training process, which permits them to discriminate between unseen samples in high performance rate (Garibaldi-Márquez et al. 2022). Andrea et al. (2017) discriminated between maize (*Zea mays* L.) and weed using CNNs. They verified LeNET, AlexNet, cNET, and sent architectures, and cNET resulted in the best performance in terms

of accuracy (95.05%) and processing time (2.34 ms). Xi et al. (2020) proposed a network called MmNet consisting of the local response normalization of AlexNet, GoogLeNet, and VGG inception models. The proposed MmNet led to an accuracy of 94.50% and a time cost of 10.369 s. Nguyen et al. (2021) used SVM and random forest (RF) techniques for disease detection in grapevine (*Vitis vinifera* L.) plants based on hyperspectral data in the range of 400 to 1,000 nm. It was observed that the SVM classifier performed better for vegetation index-wise classification, while the RF classifier showed better results for pixel-wise and image-wise classification. Garibaldi-Márquez et al. (2022) studied the use of shallow and deep learning techniques for the discrimination of crop and weeds. RGB images were captured in field conditions and different locations. The images were obtained in cornfields with three different weeds present. VGG16, VGG19, and Xception models were trained and tested, leading to accuracies of 97.93%, 97.44%, and 97.24%, respectively. In a recent work, Wang et al. (2023) took advantage of CNNs for the classification of weed species based on hyperspectral (HS) images. The study was based on a database of HS images of 40 weed species. Preprocessing was applied to the data, and the best accuracy of 98.15% was achieved.

The use of deep learning techniques and spectral data can facilitate the detection of weeds in agricultural fields. This will lead to the precise detection of weeds using a noncontact and noninvasive method. This study evaluates a method based on wavelet transform and deep networks for the separation of crops and weeds and compares it with the traditional classifiers.

Materials and Methods

Instrumentation and Measurements

Three crops, namely, cucumber (*Cucumis sativus* L.), tomato (*Solanum lycopersicum* L.), and bell pepper (*Capsicum annum* L.) and five weed species including bindweed (*Convolvulus* spp.), purple nutsedge (*Cyperus rotundus* L.), narrowleaf plantain (*Plantago lanceolata* L.), common cinquefoil (*Potentilla simplex* (Michx.)), and garden sorrel (*Rumex acetosa* L.) were used for this study. Leaves were taken from different parts of young plants of different sizes. Samples of plants were taken from plants in vegetative and flowering stages of growth. The number of samples for each growth stage was almost the same. For each plant, more than 70 samples were obtained, for a total of 626 samples. The plants (with the soil and roots) were removed from the farm and quickly transferred to the laboratory. All measurements were done under the same conditions. For illumination, one lamp of type A and one halogen lamp were used (Figure 1). Spectral reflectances in the range 380 to 1,000 nm were obtained using the spectroradiometer Specbos 1211 (JETI Technische Instrumente GmbH, Jena, Germany). This machine is a noncontact spectroradiometer that is connected to the PC via a USB port. The optical bandwidth of this spectroradiometer is 4.5 nm, and the measuring range for the illuminance is 1 to 1,500,000 Lx. As shown in Figure 1, the spectroradiometer was set at an angle of 90° in relation to the leaves, and the standard observer of 2° was used for the measurements.

Preprocessing

Statistical Pretreatment

Preprocessing for high-dimensional data normally leads to better discovery of relationships and trends of the data. In this regard, first, the beginning of the spectra that was noisy was removed.

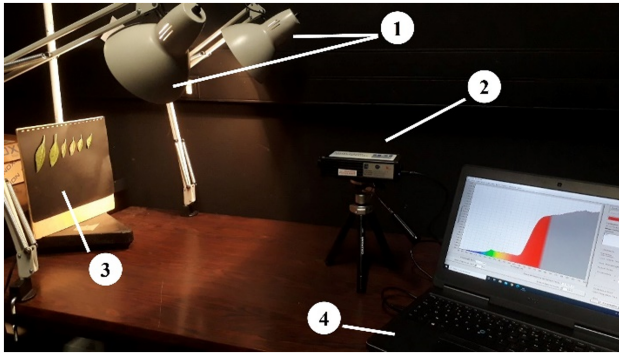


Figure 1. The measurement system and illumination setup: 1, light source; 2, spectroradiometer; 3, sample; 4, laptop computer.

Then, the data were denoised using a smoothing filter (i.e., Savitzky-Golay filter). Next, standard normal variate for applying normalization was used. Afterward, first derivative and mean centering were applied to the data.

Continuous Wavelet Transform

The preprocessing was inefficient for the data for the convolutional neural networks, as explained in the next section. In this regard, continuous wavelet transform (CWT) was used for preprocessing. CWT is used for the decomposition of a signal into wavelets. It is a perfect tool for mapping the changing properties of nonstationary signals. The basic functions of CWT are the scaled and shifted versions of the mother wavelet. The formula used for this transformation is as follows:

$$C(a, \tau) = \int \frac{1}{a} \psi\left(\frac{t - \tau}{a}\right) x(t) dt \quad [1]$$

Based on Equation 1, the wavelet $\psi(t)$ is shifted by τ and scaled by factor a . In this study, a Morse wavelet having the following formula was used:

$$\psi(\omega) = U(\omega) a_{p,\gamma} \omega^{\frac{p}{2}} e^{-\omega^\gamma} \quad [2]$$

where $U(\omega)$ represents the unit step, and a is a normalizing constant. Γ , which controls the symmetry of the wavelet, was set to 3; and p is the square root of the time–bandwidth product being in proportion to the wavelet duration was selected as $\sqrt{60}$. Hence, CWT was applied on all spectral reflectances, and a database of scalograms was constructed. These scalograms in the form 2D images were used for training the network and classification. Figure 2 provides an example of a scalogram randomly chosen from pepper plant samples.

Classification Techniques

Common Classifiers

For comparison purposes, six common classifiers were employed for the task of discrimination of crops/weeds. These techniques include LDA, QDA, linear support vector machine (LSVM), quadratic support vector machine (QSVM), ANNs, and fine k-nearest neighbors (FKNN). Table 1 presents the technical details of these methods.

Convolutional Neural Network Classifiers

GoogLeNet was utilized in this study to verify its ability to classify crops and weeds based on the spectral data. This pretrained network was used for two reasons. First, this is quite a strong network trained with a large database consisting of over 1,000 different categories. Second, use of this network saved time, as it eliminated the trial and error of building new networks. In addition, a pretrained network can be used by other researchers working in the same field.

GoogLeNet is a convolutional network that is 22 layers deep with 7 pooling layers included. There are nine inception modules stacked linearly in total. The training uses an asynchronous stochastic gradient descent with a momentum of 0.9. Initial learning rate of 1×10^{-4} , gradient threshold method of l2 norm, and maximum epochs of 20 were used for building the network. The inputs for GoogLeNet, which are the outputs of CWT, need to be RGB image arrays $224 \times 224 \times 3$. To avoid overfitting, a dropout layer was employed that randomly sets input elements to zero at a level of probability. The flowchart of the proposed method is shown in Figure 3. Morse wavelet was applied to the signals, and scalograms were extracted. Scalograms are the RGB representations of the spectral reflectances. Then, these RGB images were used for retraining the CNN. Finally, the classifier was built to carry out the classification task on new samples.

SqueezeNet is a CNN having an 18-layer depth. Like GoogLeNet, it is pretrained for more than 1,000 categories. The size of the input image is $227 \times 227 \times 3$. The weighted learning factor was set to 10. The last learnable layer was replaced with a convolutional layer with two filters. A bias learning factor of 10 was chosen. For training, the mini-batch size, maximum epochs, initial learning rate, and learning optimizer method were chosen as 10, 15, 3×10^{-4} , and a gradient descent with momentum, respectively.

Programming and Analysis

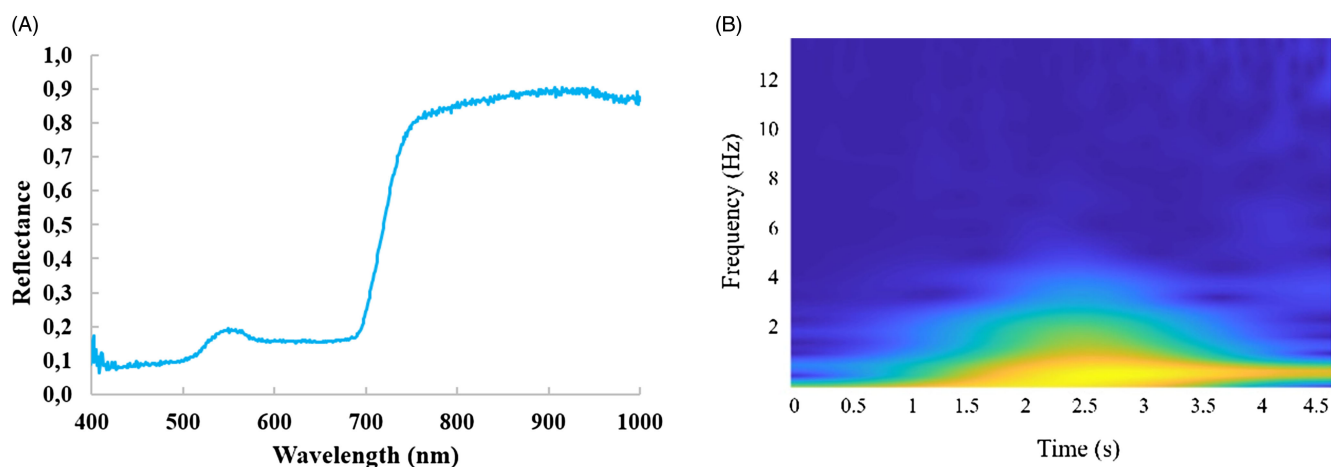
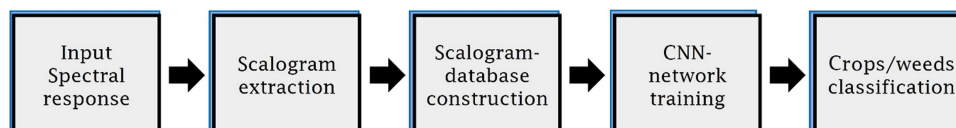
In this study, the data were randomly divided into three groups of training, validation, and testing. Therefore, 70% was used for training, 15% for validation, and 15% for testing, which was not presented to the algorithms while training (i.e., unseen data). All the programming was done using MATLAB (R2019b, MathWorks Inc., Massachusetts, USA) and MS Excel (Microsoft Office Excel, Washington, USA, 2016) software. The processing and analysis were performed on a PC with an Intel® Core™ i7 processor and 16 GB of RAM.

Results and Discussion

The spectral reflectance of leaves of crops and weeds is remarkably similar. This makes the discrimination of crops and weeds difficult. Figure 4 presents the spectral reflectance of bell pepper plant and five weeds. It is observed that use of techniques for the reduction of data volume or use of efficient classification techniques is necessary. As seen in Figure 4, most of the relevant information can be obtained from 500 to 750 nm. In the blue area of the spectrum, there are not many changes in the spectral reflectances, and absorbance is close to 1. In a study on the discrimination of weeds (i.e., spurge [*Euphorbia* spp.] and purple loosestrife [*Lythrum salicaria* L.]) from the surrounding vegetation, Hom et al. (2020) found the significant spectral bands in the same regions. Sayed Yones et al. 2019 also observed that a good discrimination of healthy/infested plants could be obtained in green and red parts of spectrum for monitoring of sugar beet

Table 1. Technical details of the common classifiers used for discrimination of plants/weeds

LDA	Linear discriminant analysis 5-fold cross-validation; covariance structure: full; gamma equal to zero
QDA	Quadratic discriminant analysis Covariance structure: diagonal
LSVM	Linear support vector machine Kernel function: linear; box constraint level: one; multiclass method: one-vs-one
QSVM	Quadratic support vector machine Kernel function: quadratic; box constraint level: one; multiclass method: one-vs-one
ANN	Artificial neural network Single hidden layer; layer size: 10; max. iteration: 1,000; activation function: rectified linear unit (ReLU)
KNN	k-Nearest neighbors Number of neighbors: one; distance metric: euclidean; distance weight: equal

**Figure 2.** A spectral reflectance of a bell pepper plant leaf (A) and its scalogram of continuous wavelet transform (CWT) colored as an RGB image (B).**Figure 3.** Block diagram of the proposed algorithm for the separation of crops and weeds.

(*Beta vulgaris* L.) infestation. In addition, in a large part of the near-infrared (NIR) area, there is little fluctuation and most of the energy has been reflected. This is expected, as plants use the visible part of the spectrum for photosynthesis and other metabolic processes (Hua et al. 2019; Mahlein et al. 2013; Su 2020).

Pretreatment

To remove random noise in the data, the spectra were smoothed. This pretreatment has been reported to be efficient in other works (Huang et al. 2021; Jiang et al. 2015; Yang et al. 2019). Afterward, they were normalized, followed by first derivative and mean centering. These techniques help to avoid irrelevant information and to better represent data trends (Türker-Kaya and Huck 2017). Recently, Amirvaresi et al. (2021) reported that mean centering and second derivative resulted in the best performance for saffron (*Crocus sativus* L.) authentication and adulteration detection based on NIR and mid-infrared (MIR) spectroscopy. In this regard, the choice of preprocessing and combination of the techniques is a critical step. This preprocessing led to a remarkable diagram representing the differences of the spectra of crops and weeds. As

Figure 5 shows, the average spectrum of crops has significant zones that are different from those of weeds. The peak of the spectrum of crops is at 735 nm, with the trough of the weed spectrum at this point, while the peak for the weeds is at 695 nm. Therefore, the spectra preprocessed by smoothing were used as the input for six traditional classifiers.

Traditional and Deep Classifiers

CWT was used for preprocessing for the deep networks. Table 2 presents the validation and test accuracies achieved by each classifier. As can be observed, the proposed method using SqueezeNet has led to complete separation of crops and weeds both for validation and test samples. However, in case of GoogLeNet, accuracy of 97.8% was achieved. It can be noted that among traditional classifiers, FKNN led to complete separation. Next, the LDA and QSVM represented better performance, both of them had a 5-fold validation accuracy of 99.6% and a test accuracy of 100%. The QDA technique ranked last, with validation and test accuracies equal to 82.5% and 86.6%, respectively. Comparison of the training time shows that the GoogLeNet (106.63 min) and then

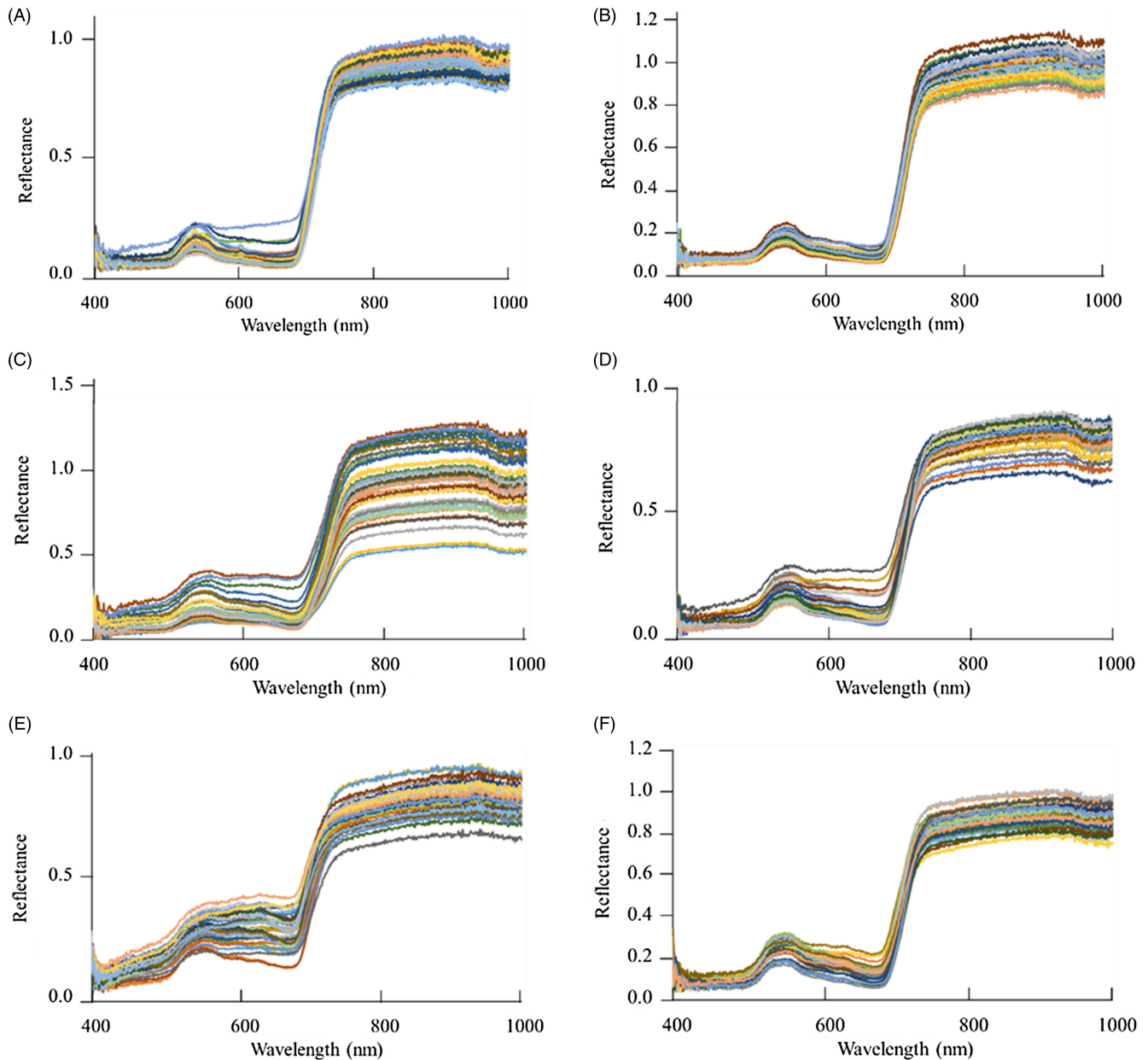


Figure 4. The spectral reflectance of plant leaves: (A) bell pepper, (B) *Convolvulus* spp., (C) *Cyperus rotundus*, (D) *Plantago lanceolata*, (E) *Potentilla simplex*, and (F) *Rumex acetosa*.

the SqueezeNet (26.85 min) required more time for training (Table 2). The great difference between the deep networks and traditional classifiers is that these networks involve the conversion of spectra to images and then use the images for training, which takes a significant time.

Compared with previous research, the performance of SqueezeNet and FKNN has been remarkable. Nidamanuri (2020) utilized ANNs for the discrimination of tea plant varieties using spectral discrimination. Here, ANN was compared with other methods, including KNN, LDA, SVMs, and normalized spectral similarity score. It was observed that SVM, as a machine learning technique, led to higher classification accuracies. Next, it was LDA that provided a high-accuracy performance. It was reported that six out of nine varieties could be discriminated with accuracies ranging between 75% and 80%. The inclusion of natural tea plants

increased the variability of the spectral data and reduced the classification accuracy. Shirzadifar et al. (2018) used soft independent modeling of the class analogy method for discrimination of three weeds based on spectral data. It was observed that the use of preprocessing was necessary for achieving proper results. Five preprocessing methods were evaluated, and second derivative was effective. The authors reported NIR area as the best area for the discrimination. The proposed method could discriminate three weed species with 100% accuracy for 63 samples. Jiang et al. (2020) proposed a graph convolutional network for crop and weed recognition. Their network achieved accuracies of 97.80%, 99.37%, 98.93% and 96.51% for four different datasets and had better results compared with AlexNet, VGG16, and ResNet-101. De Souza et al. (2020) studied the differentiation of sugarcane (*Saccharum officinarum* L.) from weeds based on spectral data and

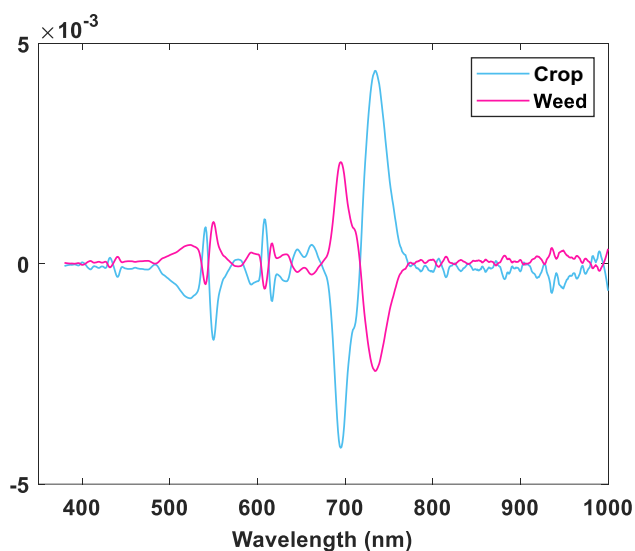


Figure 5. The average of preprocessed spectra of crops and weeds. The spectra were smoothed, normalized, and mean-centered.

using soft independent modeling. They observed that the selection of only four significant bands in VIS-NIR could lead to the same results as the whole spectrum. Their method obtained an accuracy of 97.4%. In a recent work, Su et al. (2022) mapped blackgrass (*Alopecurus myosuroides* Huds.) in wheat (*Triticum aestivum* L.) fields using multispectral images and deep learning. For the classification task, RF with Bayesian hyperparameter optimization was used. This work led to an accuracy of 93%, and the most discriminant spectral index was composed of green-NIR.

The training process with SqueezeNet in the present study shows that the original training had been very well performed (Figure 6). In this figure, the most important element is the validation curve, which has been improving and following the training data. It can be seen that from iteration 258, the network could remarkably discriminate the crops and weeds (i.e., 100% accuracy). Table 3 provides the details of training of the network. As the table indicates, in the 6th epoch, when validation accuracy reaches 100%, the validation loss is quite small, and in the 13th epoch, it reaches 0.0003. The mini-batch accuracy, which represents the accuracy of training for mini-batches or subbatches (if the whole dataset is considered to be a batch), has also been provided. The mini-batch accuracy shows that the training gets stable after the fourth epoch. Figure 7 presents the amount of loss function for each iteration. Minimizing loss function is based on the gradient descent algorithm. In every iteration, the gradient of the loss function is obtained and evaluated, and then the weights for the descent algorithm are updated. In the figure, it can be seen that the training has been going uniformly better, and the loss value for the validation data has been gradually decreasing while following the training data, showing that the learning process has been correctly performed.

The confusion matrix describing the performance of SqueezeNet has been provided in Figure 8. In this matrix, output class is the predicted classification, and the target class refers to the actual classes. It can be seen that the algorithm has randomly chosen 34 crop samples and 61 weed samples as test spectra that all have been classified correctly. Akbarzadeh et al. (2018) utilized SVM for the discrimination of crops and weeds based on spectral data. They reported that their gaussian SVM algorithm could classify the plants with a success rate of 97%. They obtained spectral data in

three wavelengths and combined the SVM with the Normalized Difference Vegetation Index (NDVI). Rock et al. (2016) performed the discrimination of eight plant species using emissive thermal infrared spectroscopy. The hyperspectral images were acquired in the range of 7.8 to 11.6 μm at 40-nm resolution. The overall accuracy of discrimination obtained was equal to 92.26%. In a recent work, Jin et al. (2022) compared GoogLeNet, MobileNet-v3, ShufNet-v2, and VGGNet for the discrimination of weeds. It was observed that ShufNet-v2 and VGGNet showed higher overall accuracies (≥ 0.999). However, among the classifiers, ShufNet-v2 and MobileNet-v3 were remarkably faster than GoogLeNet and VGGNet.

An advantage of the spectral data for the discrimination of plants is that it is light independent, as the spectral reflectance of each object is specific and acts as a fingerprint. Therefore, the spectral responses of plants can be measured on-farm and used for discrimination purposes in agricultural applications. Other techniques that have recently been employed for plant discrimination and weed detection are multispectral/hyperspectral imaging, 3D modeling of plants, and LiDAR (Sandoval et al. 2012; Andújar et al. 2018; Jarocińska et al. 2021; Jin et al. 2022; Reiser et al. 2018; Su et al. 2019). Barrero and Perdomo (2018) fused multispectral and RGB images for weed detection. As the result of their analysis, it was observed that the Normalized Green-Red Difference Index provided better features than NDVI. The preprocessing included transformation of RGB images to hue, intensity, and saturation and usage of Haar transformation. The best weed detection performance was obtained using the neural network for the percentage of detected weed area of between 80% and 108%. In the research work conducted by Özlüoymak (2020) on the usage of stereo-imaging for the detection of crops and weeds, artificial plants, including one crop and six weeds, were utilized. The proposed technique led to R^2 values of 0.962 and 0.978 for the detection of crops and weeds, respectively. In a recent study, Shahbazi et al. (2021) studied the ability of light detection and ranging (LiDAR) sensors for the detection of weeds. It was reported that the ability to detect the weeds at different scanning distances from the sensor was significantly dependent on the size of the target and its orientation toward the LiDAR. The study showed that LiDAR could detect 100% of the weeds based on their height differences with the plant canopy. Tao and Wei (2022) used a hybrid classifier based on CNN-SVM for weed recognition. For the deep CNN, the VGG network, which was trained based on true-color images, was employed. The VGG-SVM classifier resulted in an accuracy of 92.1% for the separation of winter rape (*Brassica napus* L.) seedlings and four weeds.

This study showed that spectral data are a proper tool for the discrimination of crops and weeds. The spectral reflectances of leaves of three crops (cucumber, tomato, and pepper) and five weeds (*Convolvulus* spp., *C. rotundus*, *P. lanceolata*, *P. simplex*, and *R. acetosa*) were obtained in the wavelength range of 380 to 1,000 nm. The classification performance of two deep CNNs and six common classifiers was investigated and compared. Two types of preprocessing (i.e., mathematical pretreatment and wavelet transform) were used for achieving the best performance of the techniques. It was observed that the utilization of continuous wavelet transform for dimensionality reduction of spectral data was quite successful. Results of analysis showed that the proposed method using SqueezeNet discriminated crops and weeds with 100% accuracy. This study demonstrates successful use of spectral data for accurate discrimination of various crops and weeds based on their spectral signatures. Future studies may consider the

Table 2. Comparison of validation and test accuracies for different classifiers

Method ^a	LDA	QDA	LSVM	QSVM	ANN	FKNN	GoogLeNet	SqueezeNet
Validation accuracy (%)	99.6	82.5	98.8	99.6	99.4	100.0	100.0	100.0
Test accuracy (%)	100.0	86.6	99.1	100.0	99.1	100.0	97.8	100.0
Training time (min)	0.061	0.210	0.058	0.039	0.109	0.076	106.63	26.85

^aLDA, linear discriminant analysis; QDA, quadratic discriminant analysis; LSVM, linear support vector machine; QSVM, quadratic support vector machine; ANN, artificial neural network; FKNN, fine k-nearest neighbors.

Table 3. The details of the training process of the network for each learning epoch

Epoch	Iteration	Mini-batch accuracy	Validation accuracy	Mini-batch loss	Validation loss
		%			
1	1	20	64.21	1.2562	0.7786
1	43	70	92.63	0.6065	0.2806
2	86	90	94.74	0.3808	0.1416
3	129	90	97.89	0.1119	0.0679
4	172	100	92.63	0.0076	0.1579
5	215	100	96.84	0.0079	0.0637
6	258	100	100.0	0.0005	0.0030
7	301	100	100.0	0.0016	0.0013
8	344	100	100.0	0.0026	0.0028
9	387	100	100.0	0.0016	0.0028
10	430	90	98.95	0.4685	0.0165
11	473	100	100.0	0.0079	0.0069
12	516	100	100.0	0.0005	0.0022
13	559	100	100.0	0.0001	0.0009
14	602	100	100.0	0.0000	0.0004
15	645	100	100.0	0.0000	0.0007

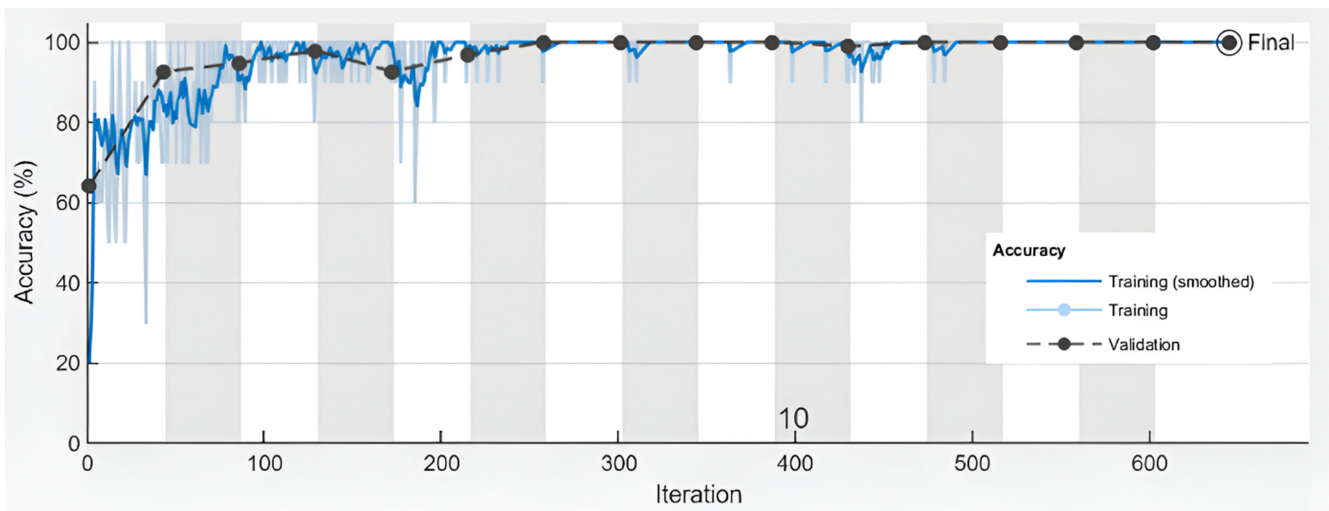


Figure 6. Diagram showing the SqueezeNet training process and accuracy per iteration.

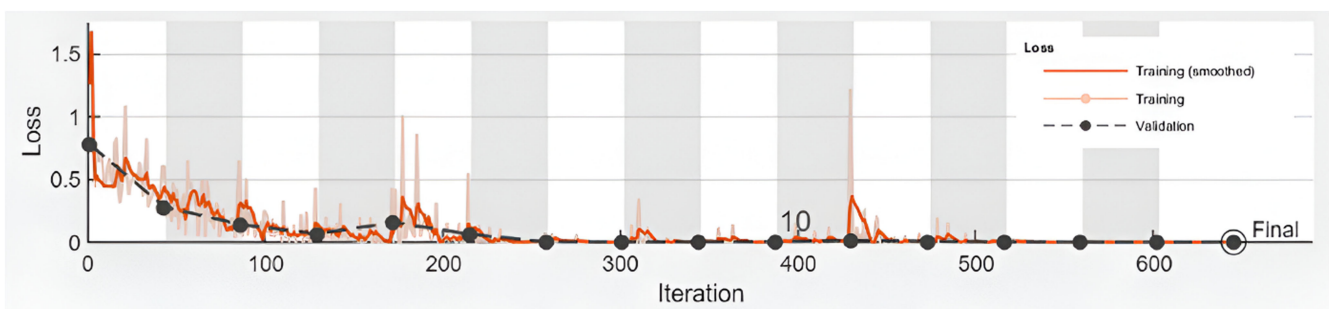


Figure 7. Diagram of loss function values per iteration during the SqueezeNet training process.

Actual class	Predicted class		
	Plant	Weed	
Plant	34 33.3 %	0 0.0 %	100 % 0.0 %
Weed	2 2.1 %	59 62.1 %	96.7 % 3.3 %
	94.4 % 5.6 %	100 % 0.0 %	97.8 % 2.2 %

Actual class	Predicted class		
	Plant	Weed	
Plant	34 35.8 %	0 0.0 %	100 % 0.0 %
Weed	0 0.0 %	61 64.2 %	100 % 0.0 %
	100 % 0.0 %	100 % 0.0 %	100 % 0.0 %

Figure 8. Confusion matrix of the networks representing true and false classifications: (A) GoogLeNet and (B) SqueezeNet.

generalization of the technique. The usage of a bigger dataset with many different types of crops and weeds will lead to the development of a robust classifier for crop/weed separation. It is suggested that the classifier be integrated into real-time weed detection systems for the evaluation of the technique in the field.

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References

- Abdulridha J, Ampatzidis Y, Ehsani R, de Castro AI (2018) Evaluating the performance of spectral features and multivariate analysis tools to detect laurel wilt disease and nutritional deficiency in avocado. *Comput Electron Agric* 155:203–211
- Acquah GE, Via BK, Billor N, Fasina OO (2016) Eckhardt LG. Identifying plant part composition of forest logging residue using infrared spectral data and linear discriminant analysis. *Sensors* 16:1375–1390
- Adelabu S, Mutanga O, Adam E, Sebego R (2013) Spectral discrimination of insect defoliation levels in mopane woodland using hyperspectral data. *IEEE J Sel Top Appl Earth Obs Remote Sens* 7:177–186
- Agüera-Vega F, Agüera-Puntas M, Agüera-Vega J, Martínez-Carricondo P, Carvajal-Ramírez F (2021) Multi-sensor imagery rectification and registration for herbicide testing. *Measurement* 175:109049
- Akbarzadeh S, Paap A, Ahderom S, Apopei B, Alameh K (2018) Plant discrimination by Support Vector Machine classifier based on spectral reflectance. *Comput Electron Agric* 148:250–258
- Amirvaresi A, Nikounezhad N, Amirahmadi M, Daraei B, Parastar H (2021) Comparison of near-infrared (NIR) and mid-infrared (MIR) spectroscopy based on chemometrics for saffron authentication and adulteration detection. *Food Chem* 344:128647
- Andrea CC, Daniel BB, Misael JB (2017) Precise weed and maize classification through convolutional neuronal networks. Pages 1–6 in 2017 IEEE Second Ecuador Technical Chapters Meeting (ETCM), 16–20 October 2017. Salinas, Ecuador: IEEE
- Andújar D, Calle M, Fernández-Quintanilla C, Ribeiro Á, Dorado J (2018) Three-dimensional modeling of weed plants using low-cost photogrammetry. *Sensors* 18:1077
- Ayala-Silva T, Beyl CA (2005) Changes in spectral reflectance of wheat leaves in response to specific macronutrient deficiency. *Adv Space Res* 35:305–317
- Barrero O, Perdomo SA (2018) RGB and multispectral UAV image fusion for Gramineae weed detection in rice fields. *Precis Agric* 19:809–822
- Bell IE, Baranoski GV (2004) Reducing the dimensionality of plant spectral databases. *IEEE Trans Geosci Remote Sens* 42:570–576
- Bradter U, O’Connell J, Kunin WE, Boffey CW, Ellis RJ, Benton TG (2020) Classifying grass-dominated habitats from remotely sensed data: the influence of spectral resolution, acquisition time and the vegetation classification system on accuracy and thematic resolution. *Sci Total Environ* 711:134584
- Buddenhagen CE, Gunnarsson M, Rolston P, Chynoweth RJ, Bourdot G, James TK (2020) Costs and risks associated with surveying the extent of herbicide resistance in New Zealand. *NZ J Agric Res* 63:430–448
- Che’Ya NN, Dunwoody E, Gupta M (2021) Assessment of weed classification using hyperspectral reflectance and optimal multispectral UAV imagery. *Agronomy* 11:1435
- Cordon G, Andrade C, Barbara L, Romero AM (2021) Early detection of tomato bacterial canker by reflectance indices. *Inf Process Agric* 9:184–194
- De Souza MF, do Amaral LR, de Medeiros Oliveira SR, Coutinho MAN, Netto CF (2020) Spectral differentiation of sugarcane from weeds. *Biosyst Eng* 190:41–46
- Durgante FM, Higuchi N, Almeida A, Vicentini A (2013) Species spectral signature: discriminating closely related plant species in the Amazon with near-infrared leaf-spectroscopy. *For Ecol Manag* 291:240–248
- Esposito M, Crimaldi M, Cirillo V, Sarghini F, Maggio A (2021) Drone and sensor technology for sustainable weed management: a review. *Chem Biol Technol Agric* 8:1–11
- Falcioni R, Moriawaki T, Pattaro M, Furlanetto RH, Nanni MR, Antunes WC (2020) High resolution leaf spectral signature as a tool for foliar pigment estimation displaying potential for species differentiation. *J Plant Physiol* 249:153161
- Fletcher RS, Reddy KN, Turley RB (2016) Spectral discrimination of two pigweeds from cotton with different leaf colors. *Am J Plant Sci* 7:2138–2151
- Garibaldi-Márquez F, Flores G, Mercado-Ravell DA, Ramírez-Pedraza A, Valentín-Coronado LM (2022) Weed classification from natural corn field-multi-plant images based on shallow and deep learning. *Sensors* 22:3021
- Gerhards R, Andujar Sanchez D, Hamouz P, Peteinatos GG, Christensen S, Fernandez-Quintanilla C (2022) Advances in site-specific weed management in agriculture—a review. *Weed Res* 62:123–133
- Gómez-Casero MT, Castillejo-González IL, García-Ferrer A, Peña-Barragán JM, Jurado-Expósito M, García-Torres L, López-Granados F (2010) Spectral discrimination of wild oat and canary grass in wheat fields for less herbicide application. *Agron Sustain Dev* 30:689–699
- Hennessy A, Clarke K, Lewis M (2020) Hyperspectral classification of plants: a review of waveband selection generalisability. *Remote Sens* 12:113
- Hom KMH, Bajwa SG, Lym RG, Nowatzki JF (2020) Discrimination of leafy spurge (*Euphorbia esula*) and purple loosestrife (*Lythrum salicaria*) based on field spectral data. *Weed Technol* 34:250–259
- Hua W, Lin Z, Guo D, Fan G, Zhang Y, Yang K, Hu Q, Zhu L (2019) Simulated long-term vegetation–climate feedbacks in the Tibetan Plateau. *Asia-Pac J Atmos Sci* 55:41–52

- Huang Y, Li J, Yang R, Wang F, Li Y, Zhang S, Wan F, Qiao X, Qian W (2021) Hyperspectral imaging for identification of an invasive plant *Mikania micrantha* Kunth. *Front Plant Sci* 12:626516
- Iqbal N, Khaliq A, Cheema ZA (2020) Weed control through allelopathic crop water extracts and S-metolachlor in cotton. *Inf Process Agric* 7:165–172
- Jarocińska A, Kopeć D, Tokarska-Guzik B, Raczko E (2021) Intra-annual variabilities of *Rubus caesius* L. discrimination on hyperspectral and LiDAR data. *Remote Sens* 13:107–129
- Jiang J, Steven MD, He R, Chen Y, Du P, Guo H (2015) Identifying the spectral responses of several plant species under CO₂ leakage and waterlogging stresses. *Int J Greenhouse Gas Control* 37:1–11
- Jiang H, Zhang C, Qiao Y, Zhang Z, Zhang W, Song C (2020) CNN feature based graph convolutional network for weed and crop recognition in smart farming. *Comput Electron Agric* 174:105450
- Jin X, Bagavathiannan M, Maity A, Chen Y, Yu J (2022) Deep learning for detecting herbicide weed control spectrum in turfgrass. *Plant Methods* 18:94
- Jones EA, Austin R, Dunne JC, Leon RG, Everman WJ (2023) Discrimination between protoporphyrinogen oxidase-inhibiting herbicide-resistant and herbicide-susceptible redroot pigweed (*Amaranthus retroflexus*) with spectral reflectance. *Weed Sci* 71:198–205
- Kamath R, Balachandra M, Prabhu S (2020) Crop and weed discrimination using Laws' texture masks. *Int J Agric Biol Eng* 13:191–197
- Le VNT, Apopei B, Alameh K (2019) Effective plant discrimination based on the combination of local binary pattern operators and multiclass support vector machine methods. *Inf Process Agric* 6:116–131
- Li Y, Al-Sarayreh M, Irie K, Hackell D, Bourdot G, Reis MM, Ghamkhar K (2021) Identification of weeds based on hyperspectral imaging and machine learning. *Front Plant Sci* 11:611622
- Liang WC, Yang YJ, Chao CM (2019) Low-cost weed identification system using drones. Pages 260–263 in *Seventh International Symposium on Computing and Networking Workshops*, 26–29 November 2019. Nagasaki, Japan: IEEE
- Liu B, Li R, Li H, You G, Yan S, Tong Q (2019) Crop/weed discrimination using a field imaging spectrometer system. *Sensors* 19:5154
- Longchamps L, Panneton B, Samson G, Leroux GD, Thériault R (2010) Discrimination of corn, grasses and dicot weeds by their UV-induced fluorescence spectral signature. *Precis Agric* 11:181–197
- Louargant M, Jones G, Faroux R, Paoli JN, Maillot T, Gée C, Villette S (2018) Unsupervised classification algorithm for early weed detection in row-crops by combining spatial and spectral information. *Remote Sens* 10:761–779
- Mahlein AK, Rumpf T, Welke P, Dehne HW, Plümer L, Steiner U, Oerke EC (2013) Development of spectral indices for detecting and identifying plant diseases. *Remote Sens Environ* 128:21–30
- Mahlein AK, Steiner U, Dehne HW, Oerke EC (2010) Spectral signatures of sugar beet leaves for the detection and differentiation of diseases. *Precis Agric* 11:413–431
- Manevski K, Manakos I, Petropoulos GP, Kalaitzidis C (2011) Discrimination of common Mediterranean plant species using field spectroradiometry. *Int J Appl Earth Obs Geoinf* 13:922–933
- Nagasubramanian K, Jones S, Singh AK, Sarkar S, Singh A, Ganapathysubramanian B (2019) Plant disease identification using explainable 3D deep learning on hyperspectral images. *Plant Methods* 15:1–10
- Nguyen C, Sagan V, Maimaitiyiming M, Maimaitijiang M, Bhadra S, Kwasniewski MT (2021) Early detection of plant viral disease using hyperspectral imaging and deep learning. *Sensors* 21:742
- Nidamanuri RR (2020) Hyperspectral discrimination of tea plant varieties using machine learning, and spectral matching methods. *Remote Sens Appl* 19:100350
- Noble SD, Brown RB (2009) Plant species discrimination using spectral/spatial descriptive statistics. Pages 82–92 in *Proceedings of the 1st International Workshop on Computer Image Analysis in Agriculture*, August 27–28. Potsdam, Germany
- Osoorio K, Puerto A, Pedraza C, Jamaica D, Rodríguez L (2020) A deep learning approach for weed detection in lettuce crops using multispectral images. *AgriEngineering* 2:471–488
- Özlüoymak ÖB (2020) Determination of plant height for crop and weed discrimination by using stereo vision system. *Tekirdağ Ziraat Fakültesi Dergisi* 17:97–107
- Pignatti S, Casa R, Harfouche A, Huang W, Palombo A, Pascucci S (2019) Maize crop and weeds species detection by using UAV VNIR hyperpectral data. Pages 7235–7238 in *IEEE International Geoscience and Remote Sensing Symposium*, 28 July 2019 – 02 August 2019. Yokohama, Japan: IEEE
- Prosperre K, McLaren K, Wilson B (2014) Plant species discrimination in a tropical wetland using in situ hyperspectral data. *Remote Sens* 6: 8494–8523
- Putra BTW (2020) New low-cost portable sensing system integrated with on-the-go fertilizer application system for plantation crops. *Measurement* 155:107562
- Rasmussen J, Azim S, Nielsen J (2021) Pre-harvest weed mapping of *Cirsium arvense* L. based on free satellite imagery—the importance of weed aggregation and image resolution. *Eur J Agron* 130:126373
- Reiser D, Vázquez-Arellano M, Paraforos DS, Garrido-Izard M, Griepentrog HW (2018) Iterative individual plant clustering in maize with assembled 2D LiDAR data. *Comput Ind* 99:42–52
- Revanasiddappa B, Arvind CS, Swamy S (2020) Real-time early detection of weed plants in pulse crop field using drone with IoT. *Int J Agric Technol* 16:1227–1242
- Rock G, Gerhards M, Schlerf M, Hecker C, Udelhoven T (2016) Plant species discrimination using emissive thermal infrared imaging spectroscopy. *Int J Appl Earth Obs Geoinf* 53:16–26
- Sabzi S, Abbaspour-Gilandeh Y (2018) Using video processing to classify potato plant and three types of weed using hybrid of artificial neural network and particle swarm algorithm. *Meas* 126:22–36
- Sandoval JD, Gor SR, Ramallo J, Sfer A, Colombo E, Vilaseca M, Pujol J (2012) Spectral signatures: a way to identify species and conditions of vegetables. Pages 308–321 in *Caivano JL, Buera MD, eds. Color in Food*. Boca Raton, FL: CRC Press
- Sayed Yones M, Amin Aboelghar M, Ali Khedry G, Massoud Ali A, Hussien Salem N, Farag E, Ahmed Mahmoud Mamon S (2019) Spectral measurements for monitoring of sugar beet infestation and its relation with production. *Asian J Agric Biol* 7:386–95
- Shafri HZ, Anuar MI, Seman IA, Noor NM (2011) Spectral discrimination of healthy and *Ganoderma*-infected oil palms from hyperspectral data. *Int J Remote Sens* 32:7111–7129
- Shahbazi N, Ashworth MB, Callow JN, Mian A, Beckie HJ, Speidel S, Nicholls E, Flower KC (2021) Assessing the capability and potential of LiDAR for weed detection. *Sensors* 21:2328
- Shanmugam S, Assunção E, Mesquita R, Veiros A, Gaspar PD (2020) Automated weed detection systems: a review. *KnE Eng* 5:271–284
- Shendryk Y, Rossiter-Rachor NA, Setterfield SA, Levick SR (2020) Leveraging high-resolution satellite imagery and gradient boosting for invasive weed mapping. *IEEE J Sel Top Appl Earth Obs Remote Sens* 13:4443–4450
- Shirzadifar A, Bajwa S, Mireei SA, Howatt K, Nowatzki J (2018) Weed species discrimination based on SIMCA analysis of plant canopy spectral data. *Biosyst Eng* 171:143–154
- Silalahi DD, Reaño CE, Lansigan FP, Panopio RG, Bantayan NC (2016) Using genetic algorithm neural network on near infrared spectral data for ripeness grading of oil palm (*Elaeis guineensis* Jacq.) fresh fruit. *Inf Process Agric* 3:252–261
- Slaven MJ, Koch M, Borger CP (2023) Exploring the potential of electric weed control: a review. *Weed Sci* 71:403–421
- Sodjinou SG, Mohammadi V, Mahama ATS, Gouton P (2021) A deep semantic segmentation-based algorithm to segment crops and weeds in agronomic color images. *Inf Process Agric* 9:355–364
- Strothmann W, Ruckelshausen A, Hertzberg J, Scholz C, Langsenkamp F (2017) Plant classification with in-field-labeling for crop/weed discrimination using spectral features and 3d surface features from a multi-wavelength laser line profile system. *Comput Electron Agric* 134:79–93
- Su J, Yi D, Coombes M, Liu C, Zhai X, McDonald-Maier K, Chen WH (2022) Spectral analysis and mapping of blackgrass weed by leveraging machine learning and UAV multispectral imagery. *Comput Electron Agric* 192:106621
- Su WH (2020) Advanced machine learning in point spectroscopy, RGB-and hyperspectral-imaging for automatic discriminations of crops and weeds: a review. *Smart Cities* 3:767–792

- Su WH, Fennimore SA, Slaughter DC (2019) Fluorescence imaging for rapid monitoring of translocation behaviour of systemic markers in snap beans for automated crop/weed discrimination. *Biosyst Eng* 186:156–167
- Subeesh A, Bhole S, Singh K, Chandel NS, Rajwade YA, Rao KVR, Kumar SP, Jat D (2022) Deep convolutional neural network models for weed detection in polyhouse grown bell peppers. *Artif Intell Agric* 6:47–54
- Sulaiman N, Che'Ya NN, Mohd-Roslim MH, Juraimi AS, Mohd-Noor N, Fazlil-Ilahi WF (2022) The application of Hyperspectral Remote Sensing Imagery (HRSI) for weed detection analysis in rice fields: a review. *Appl Sci* 12:2570
- Sunil GC, Koparan C, Ahmed MR, Zhang Y, Howatt K, Sun X (2022) A study on deep learning algorithm performance on weed and crop species identification under different image background. *Artif Intell Agric* 6:242–256
- Symonds P, Paap A, Alameh K, Rowe J, Miller C (2015) A real-time plant discrimination system utilising discrete reflectance spectroscopy. *Comput Electron Agric* 117:57–69
- Talaviya T, Shah D, Patel N, Yagnik H, Shah M (2020) Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artif Intell Agric* 4:58–73
- Tao T, Wei X (2022) A hybrid CNN–SVM classifier for weed recognition in winter rape field. *Plant Methods* 18:29
- Türker-Kaya S, Huck CW (2017) A review of mid-infrared and near-infrared imaging: principles, concepts and applications in plant tissue analysis. *Molecules* 22:168
- Ullah S, Schlerf M, Skidmore AK, Hecker C (2012) Identifying plant species using mid-wave infrared (2.5–6 μm) and thermal infrared (8–14 μm) emissivity spectra. *Remote Sens Environ* 118:95–102
- Vaiphasa C, Skidmore AK, de Boer WF, Vaiphasa T (2007) A hyperspectral band selector for plant species discrimination. *ISPRS J Photogramm Remote Sens* 62:225–235
- Wang J, Chen G, Ju J, Lin T, Wang R, Wang Z (2023) Characterization and classification of urban weed species in northeast China using terrestrial hyperspectral images. *Weed Sci* 71:353–368
- Xi QI, Li YZ, Su GY, Tian HK, Zhang S, Sun ZY, Long YA, Wan FH, Qian WQ (2020) MmNet: identifying *Mikania micrantha* Kunth in the wild via a deep Convolutional Neural Network. *J Integr Agric* 19:1292–300
- Yang W, Yang C, Hao Z, Xie C, Li M (2019) Diagnosis of plant cold damage based on hyperspectral imaging and convolutional neural network. *IEEE Access* 7:118239–118248
- Yu J, Schumann AW, Sharpe SM, Li X, Boyd NS (2020) Detection of grassy weeds in bermudagrass with deep convolutional neural networks. *Weed Sci* 68:545–552
- Zarco-Tejada PJ, Camino C, Beck PSA, Calderon R, Hornero A, Hernández-Clemente R, Kattenborn T, Montes-Borrego M, Susca L, Morelli M, Gonzalez-Dugo V (2018) Previsual symptoms of *Xylella fastidiosa* infection revealed in spectral plant-trait alterations. *Nat Plants* 4:432–439