Weed Detection in a Sunflower Field Using Supervised Learning Techniques

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Abstract. Weed growth in crops represents a challenge for farmers as this can affect plant thriving due to nutrient stealing. This paper presents a tool for weed detection in a sunflower field using computer vision techniques. To this end, regions of interest were extracted from 25 multispectral images; 20 vegetation indices were used to characterize the classes Background, Weed and Sunflower. Afterwards, Correlation Analysis (CA), Principal Component Analysis (PCA), AutoEncoder (AE), CA-PCA and CA-AE techniques were applied to create 5 datasets to train the Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Naive Bayes (NB) classifiers. The classifier that obtained the best separation between the classes Background, Weed and Sunflower was the SVM classifier applied on the PCA set based on 3 principal components, with an Accuracy of 81.5%, Precision of 81%, Recall of 81%, F1 of 81% and Cohen Kappa of 72%.

1 Introduction

Precision Agriculture (PA) aims to innovate the usual techniques for the agricultural branch by collecting and examining crop information [1]. PA uses Geographic Information Systems (GIS), Remote Sensing (RS), Spatial statistics, Farm Management Information Systems (FMIS) and Variable-Rate Technology (VRT) as monitoring strategies with the purpose of providing relevant information to improve production and output, and to reduce pollution to the environment. One such example has been its focus on sunflower harvesting. The sunflower (*H. annuus* L.) is part of the Compositae (*Astereceae*) group and is a native plant of North America [2]. One of the main uses of the sunflower is in the generation of oil due to its high content of vitamin E, which is used as an antioxidant method due to its a-, b- and γ-tocopherol content. However, there are impediments that can affect sunflower growth. These include diseases such as downy mildew (*Plasmopara halstedii*) and Phomopsis (*Diaporthe helianthi*); insects such as leafhoppers, European sunflower moth, sunflower seed weevil and sunflower stem weevil; as well as parasitic herbaceous plants such as Boomrape (*Orobanche cernua Loefl*). In addition, it is also affected by stress conditions such as drought, wild birds that usually appear 3 weeks before the seed matures and the emergence of weeds. Weeds are

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the anomaly of interest in this research, being a component of the environment that has shown to influence sunflower growth. Weeds are considered to be those plants that grow in an unwanted area and invade a crop [3]. This type of plant can be found in different environments due to its ecological adaptations and taxonomic classification. In addition, they can subsist in aquatic and ground environments and are sometimes aerial climbers. Damage that can be caused by weeds is categorized as direct and indirect losses. Direct losses consist of minimizing the quantity and quality of crop production. These losses are connected to the existence of weeds in row crops, vegetables, fruits, trees, ornamental plants, lawns, sports fields, pastures, rangelands and natural environments in general. Indirect losses, on the other hand, consist of those external factors that do not directly damage the profits obtained from the sales of the crop, but do have a cost for the population, traders and landowners. As an example, they tend to store insects, pests and cause health problems, leading to a decline in the value of the crops, generating costs for weed removal in non-agricultural areas, among other consequences. Therefore, alternatives are often implemented to counteract them [4] such as mechanical weed control like Tillage, Mowing and Flaming; chemical weed control like Herbicides; cultural weed control like Shading, Mulches and Animals; as well as weed control through Computer Vision, which is the basis of this research. Computer Vision has proven to be an opportunity gap for crops, being an example of its usefulness the work presented in [5], where potato plants that required more care due to water stress were identified; the automatic location of vegetation in karst areas such as caves with the help of an Unmanned Aerial Vehicle (UAV) [6]; the monitoring of aromatic crops [7]; the detection of weeds in canola fields using Maximum likelihood classification and deep convolutional neural networks [8]; the discrimination of weeds in crops by measuring simple morphological features of leaf shape and self-organizing neural network adapted to biological functioning for pattern detection [9]; and the weed detection with the help of the U-Net model with multispectral images taken by a UAV (unmanned aerial vehicle), the Green channel + Filtered-NIR + Normalized Difference Vegetation Index with the U-NET model [10]. In this paper, a methodology for weed detection in a sunflower field is proposed using multispectral images, vegetation indices, feature selection algorithms and classifiers such as SVM, KNN and NB.

2 Related Work

In the last decade, several research projects have been developed for the automatic detection of pests and weeds using UAVs. In 2020 Hamza et al. [8] developed a methodology to speed up the manual labeling of pixels in images of weedy crops through a 2-step procedure. In the first stage, the background and foreground were segmented by applying the Maximum likelihood classification. In the second stage, the pixels belonging to the weeds were manually labeled. The labeled elements were used to train semantic segmentation models to classify crop pixels: Background as one class and Weeds as a second class. The model that obtained the best results for weed detection was SegNeT based on ResNet-50, obtaining an average evaluation of 0.8288 in Intersection over Union (IoU) and 0.9869 in Frequency Weighted Intersection Over Union (FWIoU). The result obtained when classifying the Weed class was 0.6648 IoU and 0.9928 IoU for the elements of the Background class. In 2021 Butte et al. [5] developed a project to analyze multispectral images of a Russet Burbank potato field in Bingham County, Idaho using neural networks. Their main goal was to show the ability of automated recognition to differentiate between healthy and water-stressed plants. The model used was Retina-UNetAG which achieved an average Dice Score coefficient of 0.74 obtained between healthy classes with 0.723 and stressed classes with 0.756. This coefficient assessed the overlap between actual classes and model predictions, specifically for the identification of healthy and stressed plants. In 2023 Mertkan et al. [11] designed an algorithm for detecting weeds. To this end, a repository based on multispectral images of a sunflower field was used. Images were captured in stages, starting from the emergence of the cotyledon up to the advanced growth of the sunflower stem. The U-Net model was tested on images of the crop at the late growth stage, when chemical treatments could already be applied. The algorithm uses the Green + NIR Filtered + NDVI Index channels as input data. The classes evaluated were Soil, Crop and Weed using the IoU measure, achieving an IoU of 0.990, 0.906 and 0.753 for each respective class. The purpose of this measure is to calculate how many pixels of the prediction match the pixels of the real mask. In 2024, Seiche et al. [10] presented a comparison study between a self-made multispectral camera and the MicaSense Altum tool for weed detection. To do this, images taken by a DJI Matrice 210 UAV were used with both cameras in a corn field. The pixel-based classification of weed and crop classes required a U-Net neural network. The evaluation metrics used were Recall, which measured the ability of the model to efficiently detect positive instances for the Weed Crop and Soil classes in the datasets; Precision, which measured the number of instances detected as positive by the model that are actually positive; and the F1 Score metric, which brings the above metrics together as a balanced average into a single score. Altum reached an F1 Score of 82%, while the self-made camera achieved 76%. In the case of the Recall, Altum achieved a 75% compared to 68% for the self-made camera. However, the self-made system achieved a Precision of 90%, making it an affordable option for weed detection. Furthermore, in addition to the approaches based on Deep Learning seen above, there are other projects that work with vegetation by applying techniques based on Supervised Learning, such as those used in [23]. For example, in 2020, Lan et al. [12] conducted a research to determine the feasibility of remote sensing for Huanglongbing (HLB) in citrus orchards. For this, a multispectral ADC-lite camera mounted on a DJI Matrice M100 UAV was used to obtain multispectral photographs, their own repository was built, 20 Vegetation Indices (VIs) were used, 5 datasets were developed by applying CA, PCA, AE, CA-PCA and CA-AE, and the classifiers SVM, KNN, Logistic Regression, NB, Ensemble Learning and a Neuronal Network were trained. The evaluation metrics used were Accuracy, Recall, Precision, Specificity and F1-Score to detect healthy citrus trees from those diseased with HLB. Precision and Specificity measured the classification correctness of healthy and diseased samples; Accuracy assessed the percentage of healthy and diseased samples that were correctly classified; Recall rated the ability of the models to identify HLB affected trees; F1-Score consisted of the combination of Recall and Precision. Cohen's Kappa coefficient determined the concurrence between the different classification algorithms. The best performing classifiers were Ensemble Learning and the Neural Network, with results of 100% and 97.28% respectively, in their evaluation metrics for the detection of healthy and diseased HLB plants. In 2023, Pan et al. [6] collected multispectral image data to design a tool for vegetation detection in karst areas. To do this, they used Random Forest, SVM, Gradient Boosting Machine (GBM) and Deep Learning models to compare their efficiency in detection. Also, 16 VIs were used. The best model for vegetation detection in karst areas was GBM with a precision of 95.66%.

3 Materials

For the development of this sunflower and weed detection project in a sunflower field, a computer with a 3.42 GHz Intel Core i9 processor, a 64 GB RAM memory and a Windows 11 Pro OS was used. For the segmentation of the classes in the image sets, the *Region Of Interest (ROI) Tool* of the ENVI software version 5.3 was used. The project was implemented using Python programming language together with the following modules and libraries: OpenCV [13], Scikit-learn [14], Pandas [15], Keras [16], Tensorflow [17], Seaborn, Matplotlib [18], Numpy [19], Joblib [20] and Pickle [21]. The images used in this study were photographs of sunflower crops at an advanced stage of growth, where the plants were producing more leaves, their stalks were growing and were preparing for blooming. The repository was set up in 2016 by SAPIENZA UNVERSITÀ DI ROMA [22]. The photographs were acquired in Jesi, Italy in the infrastructure of Assam, using a multispectral camera with *Red, Green, Blue* and *NIR* channels. The images are divided into four groups: RGB, NIR, GT: greyscale images and GT_COLOR: images with the representation of the classes within the RGB model.

4 Methodology

The proposed methodology consists of 6 stages: (A) Region of Interest (ROI) extraction; (B) Dataset augmentation; (C) Calculation of Vegetation Index; (D) Dataset construction; (E) Training dataset development; and (F) Classification.

A) *ROI extraction:* In this stage, the Background, Weed and Sunflower classes were segmented using the ENVI tool. Figure 1 shows the result of extracting the regions of interest belonging to the Background, Sunflower and Weed classes from the RGB and NIR images. Figure 1a shows the *ROI* of the Background in RGB format; Fig. 1b depicts the *ROI* of the Background in NIR channel; Fig. 1c shows the *ROI* of the Sunflower in RGB format; Fig. 1d presents the *ROI* of the Sunflower in NIR channel; Fig. 1e shows the *ROI* of the Weed in RGB format; Fig. 1f presents the *ROI* of the Weed in NIR channel; Fig. 1g shows the original image in RGB format; Fig. 1h provides the original image in NIR channel.
B) *Dataset augmentation*: To increase the amount of data, the transformations of rotation, shift, mirror, brightness and contrast enhancement were applied to the extracted ROIs, resulting in a total of 125 images.

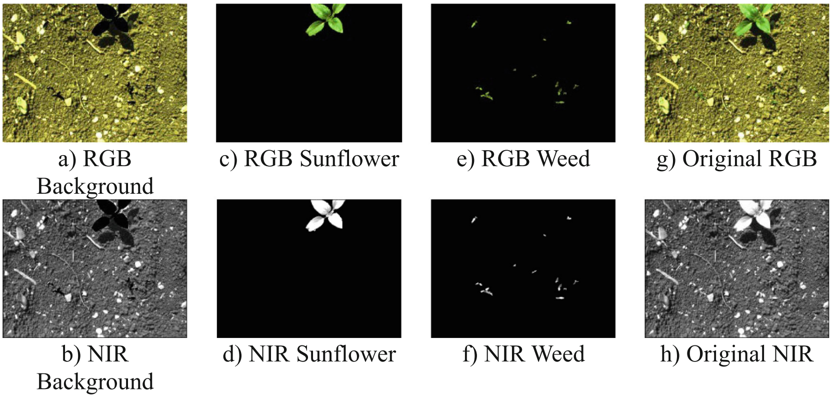

Fig. 1. ROI for each class in the different groups of images

C) *Calculation of vegetation indices (VIs)*: The purpose of the VIs is to numerically represent the values that a plant or object possesses through the colors that compose it. In this study, the 20 VIs proposed in [12] have been applied. Among the selected indices are *Normalized Difference Vegetation Index* (*NDVI*), *Structure Intensive Pigment* (*SIPI*), *Optimized Soil Adjusted Vegetation Index* (*OSAVI*) and *Ratio Vegetation Index* (*RVI*), as shown in Table 1, see Eqs. 1 to 4.

Table 1. Extract of the equations used for the calculation of vegetation indices.

Index name	Acronyms	Equations	
Normalized Difference Vegetation Index	NDVI	$(NIR - RED)/(NIR + RED)$	(1)
Structure Intensive Pigment	SIPI	$(NIR - GREEN)/(NIR + RED)$	(2)
Optimized Soil Adjusted Vegetation Index	OSAVI	$1 + L * \frac{NIR-RED}{NIR+RED+L}; L = 0.16$	(3)
Ratio Vegetation Index	RVI	NIR/RED	(4)

D) *Dataset construction*: After calculating the VIs for each class (Sunflower, Background and Weeds), a dataset was generated where each record corresponds to a pixel and the columns correspond to its VIs and to the class each record belongs to.

E) *Training dataset development*: Most studies of this type tend to use the VIs without index reduction. This is due to the fact that they only use 7 VIs. In this research, 5 datasets were generated after applying: a) Correlation Analysis (CA), b) Principal Component Analysis (PCA), c) AutoEncoder (AE), d) CA with PCA (CA-PCA) and e) CA with AE (CA-AE).

The *CA* was applied using Pearson's product moment correlation coefficient, implementing a linear transformation so that the range of the correlation was from 0 to 1, since the empirically established radius in the *CA* was from 0.96 to 1. Equation 5 shows the mathematical procedure of the analysis used, where η represents the correlation coefficient equation; X_i, X_j the comparison of vegetation indices; $cov(X_i, X_j)$ the covariance between X_i, X_j; $var(X_i)$ the variance of X_i and $var(X_j)$ the variance of X_j [1].

$$\eta = \frac{cov(X_i, X_j)}{\sqrt{var(X_i) \cdot var(X_j)}} \tag{5}$$

$$cov(X_i, X_j) = E\left[(X_i - E(X_i))(X_j - E(X_j))\right]$$

$$var(X_i) = E\left[(X_i - E(X_i))^2\right]$$

$$var(X_j) = E\left[(X_j - E(X_j))^2\right]$$

$$\eta \rightarrow \eta \times 0.5 + 0.5$$

After applying CA, it was observed that the NDVI index presented a high correlation with OSAVI, IPVI, MCARI1 and MTVI1, as the correlation values were within the established range of 0.96 to 1, therefore they were eliminated. 12 VIs were eliminated, leaving only 8 of them: NDVI, TVI, GDVI, G, CVI, MCARI1, Norm R and Norm G. After that, PCA was applied to significantly reduce the number of vegetation indices while retaining the relevant information from the original dataset. By applying *PCA*, three principal components were obtained: [0.80318816, 0.16290851, 0.01689905] giving a variance total of 0.9829957175640618.

AutoEncoder (AE) was applied, which consists of an *Encoder* and a *Decoder*, which are multilayer neural networks with dense layers. The *Encoder* consists of an input layer that receives the input dimensions (in this case, the 20 Vegetation Indices). Subsequently, the number of dimensions decreases due to fewer neurons in each layer. In the hidden layers of the *Encoder*, the *ReLU* activation function is used; this function converts negative values to 0 and keeps only positive values. Finally, in the latent space, three dimensions were obtained. The *Decoder* then reconstructs the input data again from the latent space, where the output layer reconstructs the 20 Vegetation Indices, using the *Linear* activation function. The *AE* is trained for 20 epochs with the objective of reducing as much as possible the error of reconstruction of the input information, because if the error is too high, it means that too much information is being lost and the desired error must lie within a range close to 0. The *AE* reduced the 20 indices to 3 dimensions. This analysis showed an $8.2753e{-}04$ data loss in the reconstruction of the model with the latent layer neurons. Thus, this indicates that an adequate network was built to handle the data.

CA with PCA (CA-PCA) was applied with the purpose of further reducing the dimensions of the data through the order of variances of the 3 principal components; this would result in having fewer variables to analyse, enhancing the speed of the training. The 3 principal components [0.70187342, 0.25556673, 0.01975199] of the remaining 8 *CA* indices were obtained, giving a sum of 0.9771921409345312 in variance.

Finally, CA with AE (CA-AE) was applied, reducing the 8 indices given by *CA* to only 3 dimensions, with a loss error of 0.0228.

F) *Classification.* The classification algorithms used were Support Vector Machine with a Polynomial Kernel of Degree $d = 3$, Gaussian kernel with $gamma = 0.0947$ and Linear kernel. Also, K-Nearest Neighbors was used with the Uniform Weight and Distance Weight models. And finally, Naive Bayes with the Gaussian, Multinomial and Bernoulli models. Equation 6 evaluates *Accuracy* (%), which is the proportion of correct predictions among the total predictions made. Equation 7 evaluates *Recall* (%), which is the ability of the classifier to correctly identify all positive instances. Equation 8 evaluates *Precision* (%), which is the ability of the classifier to efficiently identify positive instances out of the total number of instances predicted as positive. Equation 9 evaluates the *F1 score*, which is a combination of *Precision* and *Recall* to analyze how well the classifier is performing. Equations 10 to 12 constitute the Cohen Kappa evaluation measure that assesses the degree of concordance in the classifications.

$$Accuracy(\%) = \frac{TN + TP}{TN + TP + FN + FP} \times 100 \tag{6}$$

$$Recall(\%) = \frac{TP}{TP + FN} \times 100 \tag{7}$$

$$Precision(\%) = \frac{TP}{TP + FP} \times 100 \tag{8}$$

$$F1(\%) = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100 \tag{9}$$

$$P_0 = \frac{TN + TP}{TN + TP + FN + FP} \tag{10}$$

$$P_e = \frac{(TP + FP) * (TP + FN) + (FN + TN) * (FP + TN)}{(TP + FP + FN + TN)^2} \tag{11}$$

$$\kappa = \frac{P_0 - P_e}{1 - P_e} \tag{12}$$

5 Results

Different tests were carried out by modifying the parameters of the classifiers in order to find the model that provided the best results.

Table 2. Evaluation metrics results for the best models of each classifier.

Metric	Gaussian Kernel PCA-SVM	CA-AE KNN with Uniform Weights	Gaussian CA-PCA NB
Accuracy	0.8150	0.7969	0.7611
Precision	0.8121	0.7926	0.7652
Recall	0.8145	0.7946	0.7604
F1	0.8102	0.7931	0.7466
Cohen Kappa	0.7225	0.6951	0.6418

5.1 Experimental Results

After having experimented with different configurations, the results of the best models tested were extracted, being PCA-SVM with the Gaussian Kernel the one that obtained the best performance, as can be seen on Table 2. Table 2 shows the evaluation metrics used and the respective model corresponding to each result.

Table 2 presents the obtained results of the Gaussian Kernel PCA-SVM, CA-AE KNN with Uniform Weights and CA-PCA NB models, through the evaluation metrics Accuracy, Precision, Recall, F1 score and Cohen Kappa. In it, it is noted that the Gaussian Kernel PCA-SVM model had better performance than the rest of the models, as it obtained the highest average of the evaluation metrics: Accuracy of 81.5%, Precision of 81%, Recall of 81%, F1 of 81% and Cohen Kappa of 72%. It can be concluded that these results are due to the fact that this approach used the 3 principal components with the Gaussian Kernel on the 20 base VIs, which unlike in other models, the base amount of VIs was smaller because they had first been applied CA and then PCA or AE depending on the model, thus losing data during the process.

5.2 Comparison with Other Approaches

In the project carried out by Mertkan et al. [11] results were obtained where the classes Crop, Weed and Soil could be identified. However, they used an approach based on Deep Learning, also using 3 repositories based on sunflower fields at different stages. Instead, in this study, only a small set of images from a single sunflower repository and a Supervised Learning-based Computer Vision approach were used. On the other hand, work has been done to detect weeds in crops using the You Only Look Once (YOLO) model [24, 25]. However, the potential of the developed tool is based on the analysis applied to each pixel of the image, avoiding taking elements that do not belong to the object as YOLO does [26] and also allows the creation of classes that differentiate the state of the plant through the VIs that are applied [12].

Table 3 shows the individual evaluations of the Kernel PCA-SVM model for the classes Background, Weed and Sunflower through the Precision, Recall and F1 metrics. By averaging the 3 metrics, the Background class presented a performance of 94%, the Weed class of 70% and the Sunflower class of 79%. In these results it can be noted that the Background class was easier to detect than the Sunflower and Weed classes,

Table 3. Class evaluation of the Gaussian Kernel PCA-SVM model.

Metric	Background	Weed	Sunflower
Precision	0.9122	0.7729	0.7513
Recall	0.9712	0.6405	0.8317
F1	0.9408	0.7005	0.7895

being the latter the worst. This is due to the amount of data there was for each class. Typically, Background covers most of an image, which, unlike Sunflower or Weeds, are only found in one region, causing a lack of variability in the data, because there were not a large number of images used where these two classes could be found at different points in the same image. To improve this situation, it would be necessary to extract more regions of interest, use the GridSearchCV from the Scikit-Learn library to find the right configuration for the classifiers and further testing.

6 Conclusions

Weed emergence is a problem that significantly affects the growth of any crop, generally causing losses in both production and profit for farmers. Therefore, applying techniques that apply *Computer Vision* will facilitate the detection of this anomaly over large areas. In this case, a supervised learning approach using Vegetation Indices and CA, PCA, AE, CA-PCA and CA-AE analyses has been proposed to generate the training datasets. The SVM classifier with Gaussian, Polynomial and Linear kernels were used; the KNN classifier was used with uniform weights and distance weights models; and the NB classifier was used with Gaussian, Multinomial and Bernoulli distributions to identify weeds. To validate the results, the set was divided into 80% for training and 20% for testing. The Precision obtained for each class using the Gaussian Kernel PCA-SVM model was of 0.91 for Background, 0.77 for Weed and 0.75 for Sunflower. These results can be considered acceptable since the classifier was able to detect the three classes through the VIs that were applied directly on multispectral images. However, as a future work, it is hoped to obtain better results through experimentation and the application of performance improvement techniques, in order to be a tool that has an impact and offers a different alternative than other projects already carried out.

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