Environ Monit Assess (2022) 194:826
https://doi.org/10.1007/s10661-022-10425-w

Vegetation detection using vegetation indices algorithm supported by statistical machine learning

Umit Cigdem Turhal

Received: 14 April 2022 / Accepted: 30 August 2022 / Published online: 24 September 2022

Abstract In precision agriculture (PA), the usage of image processing, artificial intelligence, data analysis, and internet of things provides an increase in efficiency, energy, and time saving. In image processing–based applications, vegetation detection, in other words, segmentation that allows monitoring of plant growth and health as well as identification of weeds has a great importance. Vegetation indices (VIs) are widely used algorithms for segmentation. Their advantages include low computational cost and easy implementation and handling compared to the other algorithms. Nevertheless, they require a manual threshold detection that customizes the process and prevents generalization. In this study, a novel automatic segmentation method, which does not require a manual threshold detection by combining VIs with a classification algorithm, is proposed. It deals with the segmentation process as a two class classification problem (vegetation and background). As the classification algorithm, Discriminative Common Vector Approach (DCVA) that has a high discrimination power is used. Each image pixel is represented with a 3×1 dimensional vector whose elements correspond to Excess Green (ExG), Green minus Blue (GB), and Color Index of Vegetation (CIVE); VI values are obtained. Then, on the sample space accepting this pixel vector as a sample, DCVA is applied and a discriminative common vector for each class which is unique and describes that class in the best way possible is obtained and it is used for classification. Proposed segmentation method's performance is compared with Convolutional Neural Networks (CNN) and Random Forest (RF) algorithm. The proposed segmentation algorithm outperformed both CNN's and RF's performance.

U. C. Turhal (✉)
Engineering Faculty, Electric and Electronics Engineering Department, Bilecik Seyh Edebali University, Bilecik, Turkey 11210
e-mail: ucigdem.turhal@bilecik.edu.tr

Keywords Vegetation indices · Precision agriculture · Vegetation detection · Smart technologies · Image processing

Introduction

In recent years, the use of red, green, and blue (RGB) images has become quite popular in many new applications related to Precision Agriculture (PA). In PA applications performed using RGB images that are including agricultural automation such as weed detection and planting lines separation, the basic step is the image segmentation step (Philipp & Rath, 2002; Kataoka et al., 2003; Slaughter et al., 2008; Diago et al., 2012; Bao et al., 2013; Payne et al., 2014; Bargoti & Underwood, 2017; Parra et al., 2017; Tabb & Mederios, 2018). A simple planting process becomes complicated by the diversity of land areas as well as soil and plant species. Thus, the basic aim of PA applications is to facilitate this planting process by creating a sustainable production chain providing savings in energy, cost, time, etc. There are many PA applications performed on images covering large areas obtained in a short time with remote sensing systems in the literature. However, these technologies have some major disadvantages such as low resolution and unpractical usage in addition to special and costly equipment requirements (Zhang & Kovacs, 2012). Sensors used in remote sensing applications differ in terms of spatial, spectral, radiometric, and temporal resolution. In this case, according to the application, the use of sensor platforms rather than the sensor itself may be required since it will result in an increase in equipment requirements and complexity (Sishodia et al., 2020). To reduce dimensionality of hyperspectral images obtained by remote sensing, various vegetation indices algorithms and statistical machine learning (ML) algorithms such as deep learning and random forest have been applied (Chang et al., 2020; Nagasubramanian et al., 2019; Chlingaryan et al., 2018). Recently, using aerial platforms such as unmanned aerial vehicles (UAVs), and even mobile phones, high resolution RGB images are captured and the evaluation of these images with PA studies assists farmers (Hunt Jr. & Daughtry, 2018; Nex & Remondino, 2014). In PA applications such as weed mapping and variable herbicide that require about 5–50 cm spatial resolution, UAVs are preferred as they provide higher spatial resolution (<5 m) images as compared to the satellites (Castaldi et al., 2017; Fernández-Quintanilla et al., 2018).

Basically, there are two types of semantic segmentation approaches used in the literature which are color index–based and ML-based methods (Hamuda et al., 2016; Riehle et al., 2020; Wang et al., 2019; Vanyan & Khachatrian, 2021). In color index–based approach, the use of the VI in segmentation allows certain wavelengths to be highlighted in the image so that the vegetation zone can be easily distinguished from the background. The success of this method in remote sensing studies and especially under different weather conditions has been proven in various studies in the literature (Hamuda et al., 2016; Mink et al., 2018; Ruckelshausen et al., 2006; Woebbecke et al., 1995). The main advantages of these methods are more user-friendly usage and low computing power requirements compared to ML methods. Vegetation indices are obtained simply by applying mathematical operations such as addition, subtraction, and division to the corresponding pixel values of the images acquired in different spectral bands with the help of a sensor. The major advantages of VI methods are that they are easy to understand and apply in addition to allowing creation of new color indices. Because of the low computational costs and since they do not require any training stage, these methods can work in real time. However, they have some limitations that cause incorrect vegetation segmentation due to their sensitivity to illumination and image-capturing conditions. Thus, various adjustments need to be made depending on the varying illumination conditions. Another important disadvantage of these methods in a segmentation task is that they require a threshold value optimization for the final segmentation after obtaining the VI gray scale images. Since threshold determination is a sample-based application, it may vary from sample to sample which prevents the segmentation from being automated (Karcher & Richhardson, 2005). The mathematical formulas of the vegetation indices used in this study given in the "Materials and methods" section are obtained using the red (R), green (G), and blue (B) values of the images acquired from an RGB camera. However, the main disadvantages of these algorithms are the requirement of huge amount of training data and ground truth images in addition to the high computational costs and time requirements.

In this study, a novel vegetation detection method integrating VIs with ML to offer a better vegetation detection is proposed. In the proposed segmentation algorithm, VI methods are only used for data representation while ML algorithm based on feature extraction is used for segmentation. Thus, the threshold detection step that varies depending on the sample is eliminated and the segmentation is performed automatically. In order to obtain a better representation of an image pixel, ExG, GB, and CIVE VI methods are used together. Segmentation is performed using DCVA that reduces the training data set, computational cost, and time requirements significantly compared to the popular segmentation method CNN (Kamilaris & Prenafeta-Boldú, 2018; Krogh et al., 2016; Zhuang et al., 2018). Although CNN produces high accurate segmentation results, the large pre-labeled training datasets and the excessive computational power requirements emerge as to be the two important disadvantages (Kamilaris & Prenafeta-Boldú, 2018; Steen et al., 2016). On the other hand, DCVA does not require an expert-based ground truth image. DCVA reduces the feature space's dimensionality and extracts the most discriminative features for a sample class (Mu et al., 2010). While in the training stage of CNN, a 500×500 dimensional image is individually used as one input sample, in the training stage of the proposed algorithm, 250,000 input samples are obtained in response of a 500×500 dimensional image. So, our proposed algorithm can perform sufficiently even if there is only one training image sample in the dataset. This is the major superiority of the proposed algorithm compared to CNN. Thus, the disadvantages mentioned above in the paper about the usage of ML algorithms for a segmentation task have been resolved with the proposed novel hybrid segmentation algorithm.

The algorithm begins with obtaining a $3x1$ dimensional vector representation of an image pixel whose elements are corresponding ExG, GB, and CIVE vegetation indices of the image pixel. Then, as accepting these vectors as samples, DCVA is applied in this sample space. In this way, a Discriminative Common Vector that is best describing the image pixel belonging to a specific image region is obtained and it is used for detection. In the proposed vegetation detection scheme, in order to obtain a DCV for the vegetation and background image regions, first, all the original RGB images are obtained by manually cropping so as to be the vegetation and the background.

The main contributions of the paper can be summarized as follows:

- As far as we know from the literature, DCVA was used for the first time for image segmentation in this paper.
- The requirements of hardware and time were significantly reduced compared to semantic segmentation methods.
- Training dataset requirements were dramatically reduced according to semantic segmentation methods.
- There were not any expert evaluation requirements as it did not require a ground truth image for segmentation.
- The model construction and evaluation steps were fully automated.

The organization of the paper: In the next section, materials and methods including datasets and index-based data representation are given and feature extraction steps for vegetation detection are explained in detail, while in the subsequent sections, results, discussions, and, finally, conclusion are provided.

Materials and methods

Dataset

The performance of the new hybrid vegetation segmentation algorithm proposed in this study is tested on two different datasets previously used in the literature. The first dataset consists of 60 RGB images (Haug & Ostermann, 2014) obtained with the autonomous field robot Bonirob, and the second dataset consists of 39 RGB images obtained under varying illumination conditions in the Negotino region of the Republic of Macedonia (Lameski et al., 2017). Sample images of original, ground truth, and processed input for these datasets are as given in Table 1. In both studies, two new datasets were presented and their initial analysis and the initial results were reported using random forest (RF) (Breiman, 2001) algorithm and convolutional neural network (CNN) architectures, respectively. In these analyses, there are not any comparisons of the used ML algorithm. They only reported the initial analysis and initial results independent of the used ML algorithms. RF and CNN are two different types of ML algorithms just as the used algorithm DCVA in this study. The performance of the proposed algorithm is compared with both RF and CNN algorithms in two experimental studies that are using two different dataset scenario. In the first scenario, two datasets are used separately and in the second one, two datasets are combined and this combination is used so as to be a single dataset.

The vegetation and the background images are obtained by manually cropping from the original images and are resized to 500×500 dimensions as standard and tenfold cross-validation method is used for performance evaluations. To evaluate the performance of the proposed algorithm, the accuracy and the mean intersection over union (IoU) metrics, obtained from the confusion matrix, are used. Model performances are evaluated in terms of both metrics, both separately on an individual class basis and over all classes as given in Table 2. The accuracy metric is defined as the percentage of the sum of the true positive (TP) and true negative (TN) numbers that are in the confusion matrix. The mean intersection over the union metric (IoU) which is widely used in semantic segmentation applications is defined as the sum of pixel numbers common between the target and prediction masks divided by the total number of pixels in both masks (Shen & Zeng, 2019).

Table 1 Sample images including original image, mask, and input images used in the experimental studies.

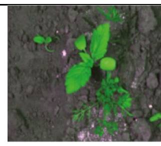
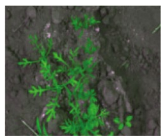
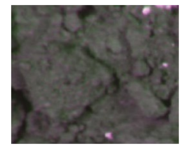
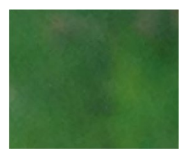
<table>
<tr><th colspan="4">Dataset 1</th></tr>
<tr><th rowspan="2">Original Sample Images</th><th rowspan="2">Ground Truth images</th><th colspan="2">Manually cropped input images</th></tr>
<tr><td>Vegetation</td><td>Background</td></tr>
<tr><td>
</td><td>
</td><td></td><td></td></tr>
<tr><th colspan="4">Dataset 2</th></tr>
<tr><th rowspan="2">Original Sample Images</th><th rowspan="2">Ground Truth images</th><th colspan="2">Manually cropped input images</th></tr>
<tr><td>Vegetation</td><td>Background</td></tr>
<tr><td>
</td><td>
</td><td></td><td></td></tr>
</table>

Table 2 Results of experimental studies for CNN-based semantic segmentation method

	Experiment	Mean IoU	Class IoU		Accuracy (%)	Class accuracy (%)	
			Background	Vegetation		Background	Vegetation
Proposed Algorithm	**1**	**0.997**	**0.997**	**0.997**	**99.88**	**99.75**	**100**
	2	**0.985**	**0.985**	**0.985**	**99.25**	**98.5**	**100**
CNN	1	0.95	0.99	0.90	99	99	99
	2	0.80	0.91	0.69	92	91	96
RF	1	0.867	0.854	0.88	86.74	85.48	88
	2	0.695	0.79	0.60	80.60	79	82.2

Index-based data representation

Simple and effective VI methods have been widely used in PA applications for evaluation of vegetation viability, growth dynamics, and detection of vegetation detection in recent years (Xue & Su, 2017). However, due to the differences in acquisition conditions of RGB images such as light spectrum combinations and resolution, there was not a generalized mathematical expression used to describe all VI. That is why an application in which the vegetation index or mathematically combined indices would be used to detect the vegetation region was determined on the basis of the image. In the literature, many VI methods detected at different wavelengths which reveal the different characteristics of the vegetation can be found (Chang et al., 2016).

In this paper, ExG, GB, and CIVE VI methods that come to the fore with their efficiency in the literature were used (Kazmi et al., 2015). In his work (Woebbecke et al., 1995), Woebbecke tested the following five VI methods using chromatic coordinates of the original RGB image to separate the vegetation region from the background. These color indices are:

$$\text{Color indices}: \ (r-g),\ (g-b),\ (\frac{g-b}{r-g}) \text{ and } (2g-r-b) \tag{1}$$

where r, g, and b values are the chromatic coordinates and given as:

$$r = \frac{R^*}{R^*+G^*+B^*},\ g = \frac{G^*}{R^*+G^*+B^*} \ and\ b = \frac{B^*}{R^*+G^*+B^*} \tag{2}$$

where $R^* = \frac{R}{R_m}, G^* = \frac{G}{G_m}$, and $B^* = \frac{B}{B_m}$, R, G, B, are the actual pixel values of a RGB image and R_m, G_m, and B_m are all equal to maximum color level 255.

Among the VI definitions given in Eq. (1), $(ExG = 2g - r - b)$, $(GB = g - b)$ indices are the Excess Green Vegetation index and Green minus Blue defined by Woebbecke et al. as in his work (Woebbecke et al., 1995). Color Index of Vegetation, CIVE, given in Eq. (3) is another vegetation index used to separate the vegetation from the background (Kataoka et al., 2003).

$$CIVE = 0.441 \times R - 0.811 \times G + 0.385xB + 18.78745 \tag{3}$$

In the vegetation index–based data representation, tensors were used in this paper. A 3rd order tensor with the dimensions of $n_1 \times n_2 \times n_3$ is an n_3 array of $n_1 \times n_2$ matrices. In the definition of a third order tensor, the terms of fibers and slices are used as shown in Fig. 1 (Kolda & Bader, 2009). A 3rd order tensor has three dimensions and it has three fibers and three slices generated by holding two of the indexes constant.

Unfolding operation is known as the process to obtain a matrix from a tensor. So, by unfolding a 3rd order tensor in mode-3 direction, a 2-dimensional matrix can be obtained as shown in Fig. 2.

In the proposed index-based segmentation algorithm, firstly, gray scale images corresponding to ExG, GB, and CIVE were obtained and gathered in the frontal slices of a 3rd tensor that was accepted as the input data of the segmentation system as shown in Fig. 3. Then, by unfolding the tensor given in Fig. 3 in mode-3 direction, the two dimensional image matrix $[A]$ was obtained.

The elements of $3x1$ dimensional column vectors of $[A]$ are given in Eq. (4). Each of these elements corresponds to ExG, GB, and CIVE vegetation index of an image pixel. This matrix is used as the input matrix for the feature extraction step given in the "Results" section. The block diagram of the data representation process using VI methods is given in Fig. 4.

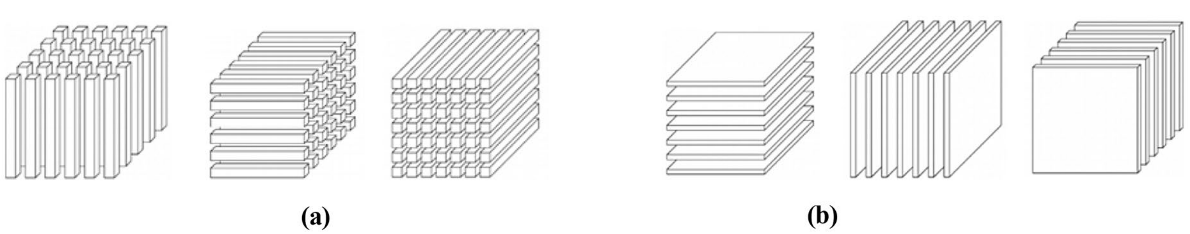


Fig. 1 **a** Row, column, and tube fibers of a tensor, left to right. **b** Horizontal, lateral, and frontal slices of a tensor, left to right (Kolda & Bader, 2009)

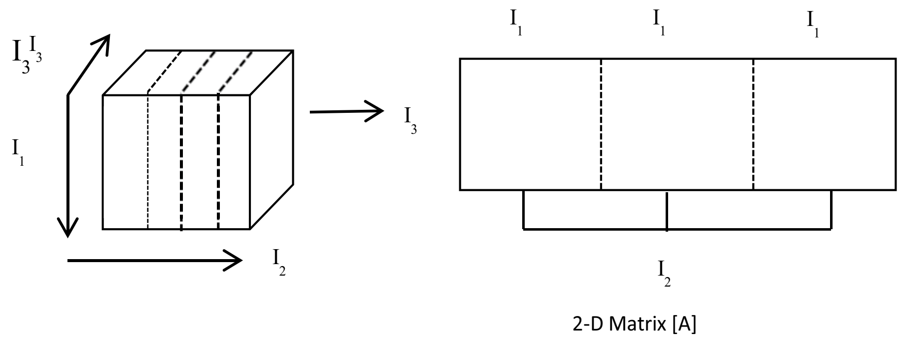


Fig. 2 Obtaining a 2D matrix by unfolding a 3rd order tensor in mode-3 direction

$$A = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \rightarrow \begin{bmatrix} ExG \\ GB \\ CIVE \end{bmatrix} \quad (4)$$

Feature extraction and classification: DCVA in sufficient data case

The proposed segmentation algorithm is actually a two-class classification algorithm that classifies the image regions as the vegetation and the background. For this classification problem, a ML algorithm DCVA is used (Cevikalp et al., 2005). DCVA first obtains the intra class scatter matrix (S_W) of all classes as given in Eq. (5). Since the case is insufficient data, (S_W) has a null space. By performing the eigen-analysis of (S_W), its null space is obtained. The eigenvectors that span the null space ($V^{\perp}$) are obtained as $\mathrm{V}^{\perp} = \mathrm{span}\left\{\alpha_k \backslash S_W \alpha_k = 0, k = r+1, .., d\right\}$.

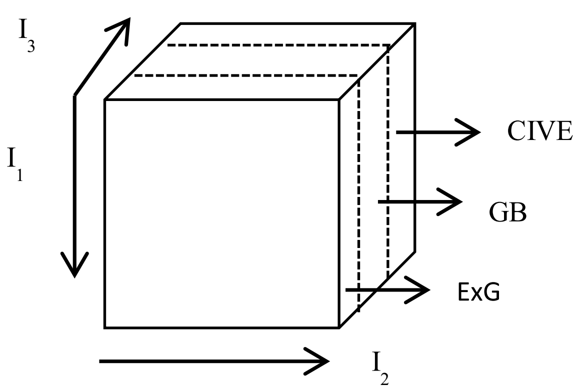


Fig. 3 The 3rd tensor that its frontal slices are composed from the VI: ExG, GB, and CIVE

$$S_W = \sum_{i=1}^{C} \sum_{j=1}^{m} (x_j^i - \mu_i)(x_j^i - \mu_i)^T \quad (5)$$

where $\mu_i = {}^1/_m \sum_{j=1}^{m} x_j^i, i = 1, \ldots, C$ and C is the total data class number. Then, by projecting any vector from each class onto the null space of (S_W), a unique common vector is obtained for each data class. By gathering the eigenvectors that span the null space ($V^{\perp}$) in the columns of the matrix $\overline{Q} = \left[\alpha_{r+1} \cdots \alpha_d \right]$, a transformation matrix is obtained. The column vectors of this transformation matrix span the indifference space of the original sample space. Then, a common vector for each class is obtained by projecting any vector from each class onto the indifference subspace as given in Eq. (6).

$$x_{com}^i = \overline{Q}\overline{Q}^T x_j^i \quad (6)$$

where $x_j^i \in R^d$ is any sample vector from the i^{th} class in the original sample space.

After obtaining the common vectors for all classes, the scatter matrix of these common vectors (S_{com}) is obtained as given in Eq. (7). A (W) whose column vectors consist of the optimal projection vectors which maximize (S_{com}) and meet the criteria in Eq. (8) is constructed. Then, a unique DCV for each class is obtained by using (W).

$$S_{com} = \sum_{i=1}^{C} (x_{com}^i - \mu_{com})(x_{com}^i - \mu_{com})^T \quad (7)$$

where μ_{com} is the mean vector of the class common vectors ($\mu_{com} = {}^1/_C \sum_{i=1}^{C} x_{com}^i$).

$$J(W_{opt} = argmax_W \| W^T S_{com} W \| \quad (8)$$

DCVA procedure defined up to here is the application of this method in case of insufficient data. But, in our

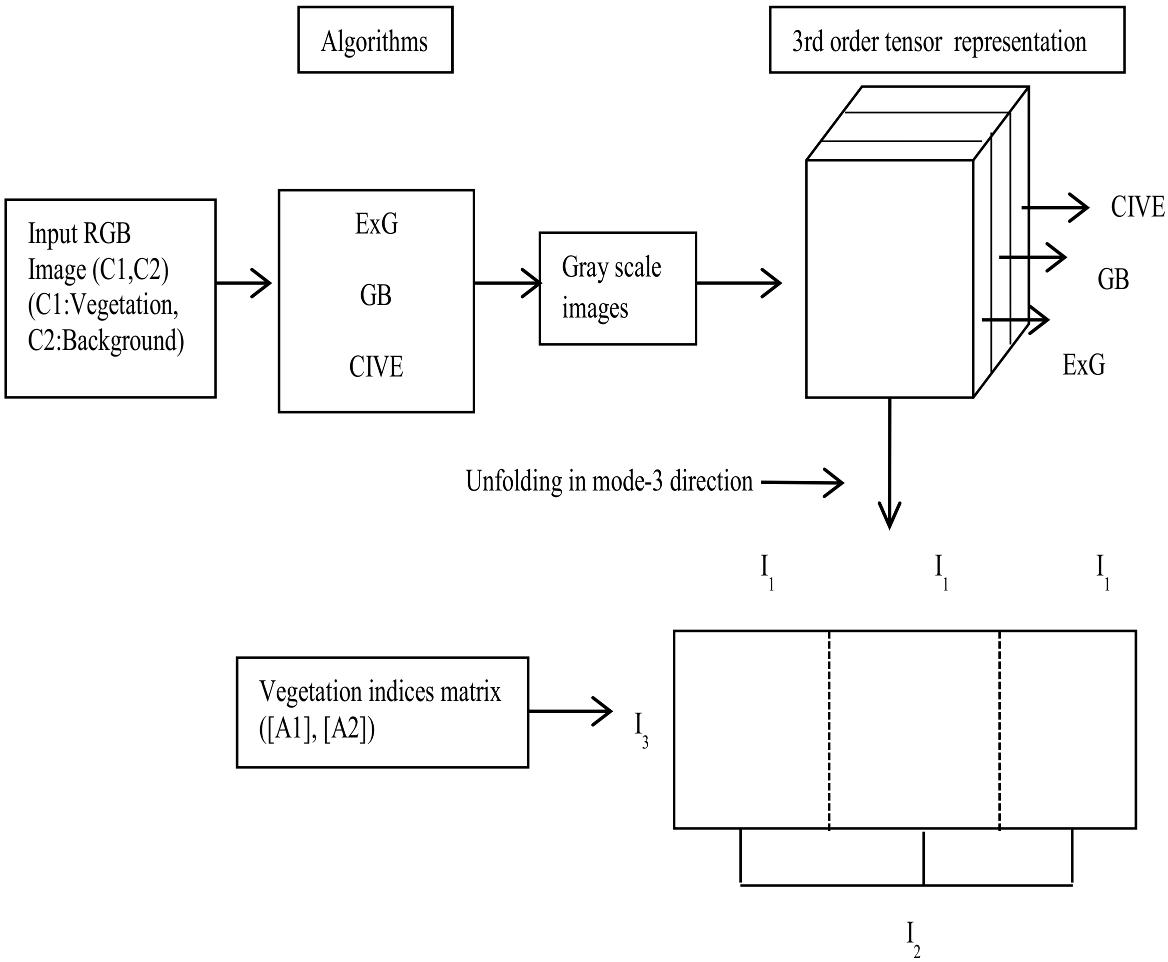


Fig. 4 The proposed data representation process using VI

study, the sufficient data case is relevant, namely, the sample dimension is less than the sample number. In this case, the null space of (S_W) disappears because there will not be any zero eigenvalue of (S_W); thus, DCVA could not be applied. However, Onal and Turhal in their study, given in Onal and Turhal (2021), performed the extension of DCVA that can be used in case of sufficient data. In their study, the researchers showed that the eigenvectors (u_j) whose eigenvalues (λ_j) satisfy the following criterion given in Eq. (9) span the difference and indifference subspaces $u_j \in R^d, j = 1, 2, .., k-1 (k-1 < d)$ and $u_j \in R^d, j = k, k+1, .., d$, respectively.

$$(\sum_{j=k}^{d} \lambda_j)/(\sum_{j=1}^{d} \lambda_j) < L \tag{9}$$

where the 5% value for L in Eq. (8) has been indicated to be giving good performance (Swets & Weng, 1996). Thus, by gathering the eigenvectors that span the indifference subspace in the columns of a matrix, $\overline{Q} = \left[u_k \cdots u_d \right]$, a transformation matrix that represents the indifference subspace of the original sample space can be obtained. Then, a common vector for each class is obtained by projecting the average vector (x^i_{ave}) of that class onto the indifference subspace as given in Eq. (10).

$$x^i_{com} = \overline{Q}\overline{Q}^T x^i_{ave} \tag{10}$$

In sufficient data case, after obtaining the common vectors, the scatter matrix (S_{com}) given in Eq. (7) and the optimal projection vectors of it can be obtained as in the insufficient data case. And these optimal projection vectors are used to find the DCV for each class. For the testing step, the test data is projected onto the subspace defined by these optimal projection vectors satisfying Eq. (8) and a remaining vector (Rem_{test}) is obtained for the test data by this projection. Then, the Euclidian distances between the DCV belonging to each class and the remaining test vector are obtained, and the test data is assigned to the class that has the minimum distance. The flowchart of the overall vegetation detection algorithm is as given in Fig. 5.

Results

The classification/segmentation task is a supervised learning algorithm so it requires a classification model construction step using a ML algorithm. In the model construction step, a training set composed from the samples whose class information is previously known is used. Once the model is constructed, then, using a test set that is composed from the samples that are not used in the model construction step, the classification/segmentation performance of the model is evaluated. The required, targeted classification results in the test dataset are called ground truth. The performance evaluation in ML-based segmentation problems is performed using some metrics such as accuracy and intersection-over-union (IoU) score. Accuracy is defined as the proportion of the correctly classified/segmented sample numbers to the whole test number. IoU is defined as the proportion of the intersection of the ground truth with the classification/segmentation result to the union of these two.

The segmentation results in terms of accuracy and mean IoU obtained for the proposed algorithm, CNN and RF, of the two experimental studies performed on two different datasets are as given in Table 2. In the first experimental study, vegetation detection is performed using each of the two datasets separately and in the second one, the two datasets are combined and this combination is used so as to be a single dataset. It achieved extremely high segmentation results for proposed novel hybrid segmentation algorithm in both experiments, and in both experiments, proposed algorithm outperformed CNN and RF.

The results are evaluated in terms of both mean IoU and accuracy for both the two classes, the vegetation and the background, separately and for overall. According to Table 2, it can be seen that for all the methods, the first experiment results are better than the second experiment results. It is thought that the reason for this is the data set used in the first experiment is composed from only one data set. In other words, the training set and the test set samples include only one data set sample.

However, in the second experiment, the two data sets are mixed. While the samples from one data set are used as the training set, samples from the other data set are used as the test set. Nevertheless, the success difference of the two experiments in terms of the mean IoU score and the accuracy, for the proposed method, is obtained as too small. While the performance difference for mean IoU is obtained as 1.2% in the proposed study, it is obtained 1.5% and 1.7% for CNN and RF, respectively. This shows the superiority of the proposed method over CNN and RF. For both of the two experiments, the best success results are obtained for the proposed method. In the first experiment, for the proposed method, 99.7% mean IoU is obtained; in the second experiment, it is obtained at 98.5%. Mean IoU for CNN and RF, is 95% and 86.7% in the first experiment and is 80% and 69.5% in the second experiment respectively.

Discussion

In this study, the application of the DCVA method, which is a statistical ML classification method in a sample space where image pixels are represented by three different vegetation indices, is presented for vegetation segmentation. Considering the structure of the data, the sample space is defined as a three-dimensional space. Each of these dimensions are attributes corresponding to each of the three vegetation indices. As the number of samples is much smaller than the sample size, our classification problem corresponds to a sufficient data case where the size of the samples is much greater than the number of sample attributes. In other words, the data set used is a small or medium-sized dataset that is not large in terms of the number of attributes.

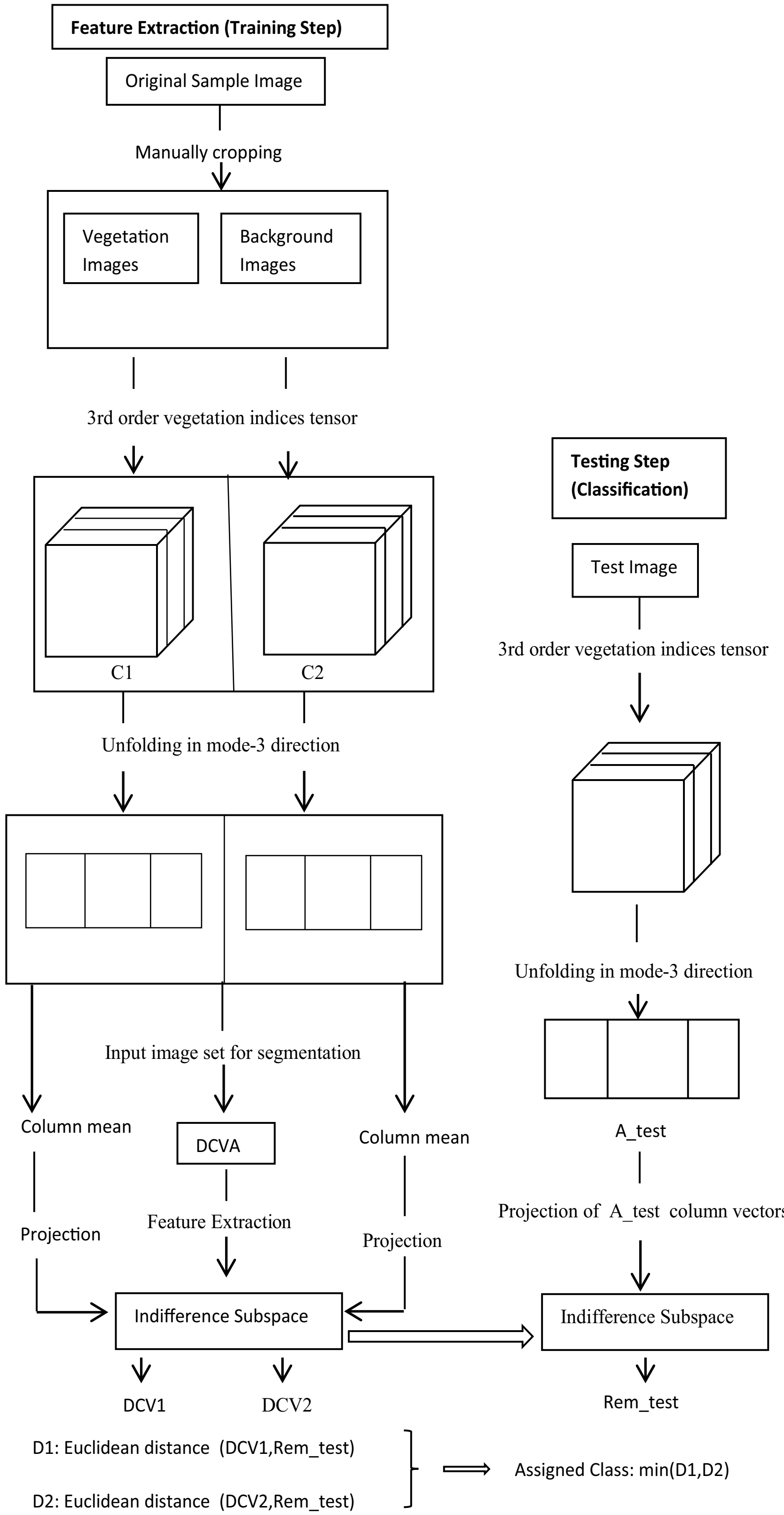


Fig. 5 Flowchart of the proposed overall segmentation algorithm

Obtained experimental segmentation results show that the presented method gives better results compared to popular ML algorithms CNN and RF in segmentation problems. This is due to the fact that it works better in statistical ML classification algorithms instead of ML algorithms due to the characteristics of the dataset used (Ij, 2018). RF and CNN are both leading ML methods used for land cover classification. When they are compared with more traditional classifiers, they achieve similar or superior classification accuracy with better computational performance. For these reasons, in a segmentation task, RF and CNN methods are often used for benchmarks (Boston et al., 2022).

In this sense, if we compare statistical ML methods (DCVA) and ML algorithms (CNN, RF), both methods are used successfully in classification problems. However, they differ in terms of the dataset features they have successfully processed and their perspectives on the classification problem. ML algorithms focus on finding patterns in big data when performing classification, so it is useful in case of insufficient data, that is, when the number of samples is less than the number of sample attributes. It is not needed to know the details of sample space to implement ML; the only thing that matters is which of the sample attributes used is more useful. This type of generalization is also useful for wide data where the sample attributes are greater than the number of samples. However, statistical methods attempt to solve the classification problem by inference obtained through the creation and fitting of a project-specific probability model. Statistical ML methods are designed for the sufficient data case where the number of samples is much larger than the number of sample attributes, unlike ML algorithms. As the number of input variables and the possible relationships between them increases, the model that captures these relationships becomes more complex. In other words, an increase in data complexity can make classical statistical inference less traceable. At the same time, the model is open to improvement in order to prevent misclassifications caused by noise (Ij, 2018).

For all these reasons, since the sample space used in the vegetation segmentation algorithm presented in this study corresponds to the sufficient data case, the presented method obtained much better segmentation results than the popular ML algorithms CNN and RF. There is no sharp boundary between statistical ML methods and ML algorithms. Statistics requires choosing a model that combines information about the classification problem, while ML requires choosing a model that classifies based on empirical capabilities. In the future studies, it is aimed to develop a more robust classification algorithm invariant of dataset features in which DCVA is integrated into CNN (Ij, 2018).

Conclusions

In this study, a novel vegetation detection/segmentation method that integrates VIs by statistical ML is proposed. In this segmentation task, the DCVA algorithm is used as the statistical ML and this is the first study in the literature that DCVA is used for image segmentation. The proposed method's performance is compared with CNN and RF that are popular ML algorithms used in image segmentation. It can be seen from the experimental studies' results that the proposed method outperforms both CNN and RF. The reason for this is that the dataset used in this study satisfies the sufficient data case in which the sample number is more than the sample dimension. This is explained in the "Discussion" section in detail based on the features of statistical ML and other ML algorithms. In the future studies, it is aimed to develop more robust segmentation algorithms invariant to dataset integrating statistical ML methods into ML algorithms. It is hoped that this study will be a guide to the researchers who study in this field.

Data availability The datasets analyzed during the current study are available in the [CWFID—Crop Weed Field Image Dataset] repository, [https://github.com/cwfid], and in the [lameski/rgbweeddetection] [https://github.com/lameski/rgbweeddetection].

Declarations

Competing interests The author declares no competing interests.

References

Bao, X., Javanbakhti, S., Zinger, S., & Wijnhoven, R. (2013). Context modeling combined with motion analysis for moving ship detection in port surveillance. *Journal of Electronic Imaging, 22*(4), 041114. https://doi.org/10.1117/1.JEI.22.4.041114

Bargoti, S., & Underwood, J. P. (2017). Image segmentation for fruit detection and yield estimation in apple orchards. *Journal of Field Robotics*, *34*(6), 1039–1060. https://doi.org/10.1002/rob.21699

Boston, T., Van Dijk, A., Larraondo, P. R., & Thackway, R. (2022). Comparing CNNs and random forests for Landsat ımage segmentation trained on a large proxy land cover dataset. *Remote Sensing, 14*(14), 3396. https://doi.org/10.3390/rs14143396

Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5–32. https://doi.org/10.1023/A:1010933404324

Castaldi, F. F., Pelosi, F., Pascucci, S., & Casa, R. (2017). Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize. *Precision Agriculture, 18*, 76–94. https://doi.org/10.1007/s11119-016-9468-3

Cevikalp, H., Neamtu, M., Wilkes, M., & Barkana, A. (2005). Discriminative common vectors for face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 27*(1), 4–13. https://doi.org/10.1109/TPAMI.2005.9

Chang, C. Y., Zhou, R., Kira, O., Marri, S., Skovira, J., & Gu, L. (2020). Sun, Y. An Unmanned Aerial System (UAS) for concurrent measurements of solar induced chlorophyll fluorescence and hyperspectral reflectance toward improving crop monitoring. *Agricultural and Forest Meteorology, 294*, 1–15. https://doi.org/10.1016/j.agrformet.2020.108145

Chang, L., Peng-Sen, S., & Shi-Rong, L. (2016). A review of plant spectral reflectance response to water physiological changes. *Chinese Journal of Plant Ecology, 40*(1), 80–91. https://doi.org/10.17521/cjpe.2015.0267

Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture*, *151*, 61–69. https://doi.org/10.1016/j.compag.2018.05.012

Diago, M.-P., Correa, C., Millán, B., Barreiro, P., Valero, C., & Tardaguila, J. (2012). Grapevine yield and leaf area estimation using supervised classification methodology on RGB images taken under field conditions. *Sensors, 12*, 16988–17006. https://doi.org/10.3390/s121216988

Fernández-Quintanilla, C., Peña, J. M., Andújar, D., Dorado, J., Ribeiro, A., & López-Granados, F. (2018). Is the current state of the art of weed monitoring suitable for site-specific weed management in arable crops? *Weed Research, 58*, 259–272. https://doi.org/10.1111/wre.12307

Hamuda, E., Glavin, M., & Jones, E. (2016). A survey of image processing techniques for plant extraction and segmentation in the field. *Computers and Electronics in Agriculture., 125*, 184–199. https://doi.org/10.1016/j.compag.2016.04.024

Haug, S., & Ostermann, J. (2014). A crop/weed field image dataset for the evaluation of computer vision based precision agriculture tasks. *European Conference on Computer Vision* (pp. 105–116). Springer.

Hunt, E. R., Jr., & Daughtry, C. S. (2018). What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? *International Journal of Remote Sensing, 39*(15–16), 5345–5376. https://doi.org/10.1080/01431161.2017.1410300

Ij, H. (2018). Statistics versus machine learning. *Nature Methods, 15*(4), 233.

Kamilaris, A., & Prenafeta-boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture, 147*, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Karcher, D. E., & Richardson, M. D. (2005). Batch analysis of digital images to evaluate turfgrass characteristics. *Crop Science, 45*, 1536–1539. https://doi.org/10.2135/cropsci2004.0562

Kataoka, T., Kaneko, T., Okamoto, H., & Hata, S. (2003). Crop growth estimation system using machine vision. *In: IEEE/ASME International Conference on Advanced Intelligent Mechatronics* (pp. 1079–1083). Kobe, Japan: IEEE. https://doi.org/10.1109/AIM.2003.1225492

Kazmi, W., Garcia-Ruiz, F. J., Nielsen, J., Rasmussen, J., & Andersen, H. J. (2015). Detecting creeping thistle in sugar beet fields using vegetation indices. *Computers and Electronics in Agriculture, 112*, 10–19. https://doi.org/10.1016/j.compag.2015.01.008

Kolda, T. G., & Bader, B. W. (2009). Tensor decompositions and applications. *SIAM Re-View, 51*(3), 455–500. https://doi.org/10.1137/07070111X

Krogh, A., Dyrmann, M., Karstoft, H., Nyholm, R., & Gislum, R. (2016). Semantic segmentation of mixed crops using deep convolutional neural network. *In: CIGR-AgEng Conference* (pp. 1–6).

Lameski, P., Zdravevski, E., Trajkovik, V., & Kulakov, A. (2017). Weed detection dataset with RGB images taken under variable light conditions. *In International Conference on ICT Innovations* (pp. 112–119). Springer, Cham. https://doi.org/10.1007/978-3-319-67597-8_11

Mink, R., Dutta, A., Peteinatos, G. G., & Sökefeld, M. (2018). Multi-temporal site-specific weed control of Cirsium arvense (L.) scop. and Rumex crispus L. in maize and sugar beet using nmanned aerial vehicle based mapping. *Agriculture, 8*, 1–14. https://doi.org/10.3390/agriculture80500650

Mu, M., Ruan, Q., & Shen, Y. (2010). Palmprint recognition based on discriminative local binary patterns statistic feature. *In 2010 international conference on signal acquisition and processing* (pp. 193–197). IEEE.

Nagasubramanian, K., Jones, S., Singh, A. K., Sarkar, S., & Singh, A. (2019). Ganapathysubramanian, B. Plant disease identifcation using explainable 3D deep learning on hyperspectral images. *Plant Methods, 15*, 1–10. https://doi.org/10.1186/s13007-019-0479-8

Nex, F., & Remondino, F. (2014). UAV for 3D mapping applications: A review. *Applied Geomatics, 6*(1), 1–15. https://doi.org/10.1007/s12518-013-0120-x

Onal, Y., & Turhal, U. C. (2021). Discriminative common vector in sufficient data case: A fault detection and classification application on photovoltaic arrays. *Engineering Science and Technology, an International Journal, 24*(5), 1168–1179. https://doi.org/10.1016/j.jestch.2021.02.017

Parra, A., Boutin, M., & Delp, E. J. (2017). Automatic gang graffiti recognition and interpretation. *Journal of Electronic Imaging, 26*(5), 051409. https://doi.org/10.1117/1.JEI.26.5.051409

Payne, A., Walsh, K., Subedi, P., & Jarvis, D. (2014). Estimating mango crop yield using image analysis using fruit at 'stone hardening' stage and night time imaging.

Computers and Electronics in Agriculture, 100, 160–167. https://doi.org/10.1016/j.compag.2013.11.011

Philipp, I., & Rath, T. (2002). Improving plant discrimination in image processing by use of different colour space transformations. *Computers and Electronics in Agriculture, 35*(1), 1–15. https://doi.org/10.1016/S0168-1699(02)00050-9

Riehle, D., Reiser, D., & Griepentrog, H. W. (2020). Robust index-based semantic plant/background segmentation for RGB-images. *Computers and Electronics in Agriculture, 169*, 105201. https://doi.org/10.1016/j.compag.2019.105201

Ruckelshausen, A., Klose, R., Linz, A., Marquering, J., Thiel, M., & Tölke, S. (2006). Autonome Roboter zur Unkrautbekämpfung. *Journal of Plant Diseases and Protection*, 173–180.

Shen, F., & Zeng, G. (2019). Semantic image segmentation via guidance of image classification. *Neurocomputing, 330*, 259–266. https://doi.org/10.1016/j.neucom.2018.11.027

Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. *Remote Sensing, 12*(19), 3136. https://doi.org/10.3390/rs12193136

Slaughter, D. C., Giles, D. K., & Downey, D. (2008). Autonomous robotic weed control systems: A review. *Computers and Electronics in Agriculture, 61*(1), 63–78. https://doi.org/10.1016/j.compag.2007.05.008

Steen, K. A., Christiansen, P., Karstoft, H., & Jørgensen, R. N. (2016). Using deep learning to challenge safety standard for highly autonomous machines in agriculture. *Journal of Imaging,* 2–9. https://doi.org/10.3390/jimaging2010006

Swets, D. L., & Weng, J. (1996). Using discriminant eigenfeatures for image retrieval. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 18*, 831–836. https://doi.org/10.1109/34.531802

Tabb, A., & Medeiros, H. (2018). Automatic segmentation of trees in dynamic outdoor environments. *Computers in Industry, 98*, 90–99. https://doi.org/10.1016/j.compind.2018.03.002

Vanyan, A., & Khachatrian, H. (2021). Deep semi-supervised ımage classification algorithms: A survey. *Journal of Universal Computer Science, 27*(12), 1390–1407. https://doi.org/10.3897/jucs.77029

Wang, A., Zhang, W., & Wei, X. (2019). A review on weed detection using ground-based machine vision and image processing techniques. *Computers and Electronics in Agriculture, 158*, 226–240. https://doi.org/10.1016/j.compag.2019.02.005

Woebbecke, D. M., Meyer, G. E., Von Bargen, K., & Mortensen, D. A. (1995). Color indices for weed identification under various soil, residue, and lighting conditions. *Transactions of the ASAE, 38*, 259–269. https://doi.org/10.13031/2013.27838

Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of sensors*. https://doi.org/10.1155/2017/1353691

Zhang, C., & Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: A review. *Precision Agriculture, 13*(6), 693–712. https://doi.org/10.1007/s11119-012-9274-5

Zhuang, S., Wang, P., & Jiang, B. (2018). Segmentation of green vegetation in the field using deep neural networks. *In 2018 13th World Congress on Intelligent Control and Automation (WCICA)*, 509–514. https://doi.org/10.1109/WCICA.2018.8630376

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.