Feature Based Plant Seedlings Classification

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Abstract. In this work, we study the application of image features in the plant classification task. The researched dataset was created at Aarhus University Flakkebjerg Research. It is aimed to let researchers try different approaches in plant species categorization. The feature-based approach requires attention. It allows us to perform classifying using less computational resources. The features usage is motivated by the purpose: we need to distinguish weeds from other plants, and we can do that by selecting the defining features of all classes of plants. The proposed method combines image thresholding, feature selection and feature extraction for the further multiclass classification by such well-known machine learning algorithms as Support Vector Machines, K-Nearest Neighbours, Decision Tree and Naive Bayes. To a greater extent, we use computer vision algorithms for the image processing step. The main classification method we choose for the task is support vector machines, it showed the best performance among other tested algorithms.

Keywords: Image processing · Feature extraction · Computer vision.

1 Introduction

The demand for agricultural products is increasing day by day, as the population of the Earth is growing. Even though people work on plant classification algorithms, approaches are still not as efficient and robust as desired. A significant part of this work has still been done by people. The question arises of the efficiency with which human resources are used. We will use exhaustible natural resources wisely and increase harvests if we automatize quality assurance, which objectives are to detect and distinguish weeds among the variety of crop seedlings.

All this naturally leads to the idea of automation of the classification process with the help of machine learning algorithms. From recent experience, neural networks are well suited for image processing, but we have to pay for it by computational costs. On the other hand, we could use less costly algorithms, but they require finer tuning to achieve comparable results.

A feature-based method is a popular approach in image classification problems, there are many advantages and results with a good performance in many related pieces of research, as in [12], [15]. The main idea of this method is to process the only relevant information of an image, and to reduce the feature space

dimension as much as possible. Likewise, dimensionality reduction is the way of solving the curse of dimensionality problem formulated by Richard Bellman in 1957 [1]. The suggested method is described in [9].

The goal of our work is to implement segmentation and classification of a specific type of datasets for lower processing time and computational complexity. In this paper, we study binary classifier capabilities on the dataset [8] consisting of images of 12 species and containing the most common weed species in Danish agriculture.

2 Materials and methods

2.1 Data

The considered dataset is a part of the database that has been recorded at the Aarhus University Flakkebjerg Research station in the collaboration between the University of Southern Denmark and Aarhus University. Images are available to researchers at https://vision.eng.au.dk/plant-seedlings-dataset/. The specifics of this dataset is that recorded plants are in different growth stages since detecting a weed in its early stage is the thing which makes the task problematic.

The dataset contains 960 unique plant images of 12 species. The sizes of plant classes are not balanced among themselves—they range from 221 to 654 labeled samples for each class. Original images are cropped by plant boundaries, but their resolutions vary from 50x50px to 2000x2000px. Also, images have different backgrounds—some of them are on the ground, other are on the marked paper.

2.2 Data preprocessing

Resolution reducing

Resolution reducing We reduce the resolution of all images to the same resolution 200x200px using the bilinear interpolation. The main idea of the bilinear interpolation is that a new image pixel is defined as the weighted sum of neighboring pixels of the original image. It helps to decrease computational complexity and build normalized features [5].

Segmentation The objects of our study are plants, and they are painted green. Therefore, we can create a mask that filters the range of green channel and ignores the other pixels. For these purposes, the HSV (Hue Saturation Value) color model is a suitable representation [13]. In the BGR format, the value of each component depends on the amount of light hitting the object. HSV allows us to distinguish between the image color and brightness. We set the lower and upper bounds of the green color using HSV representation. Then we merely mark the pixels in the green range and get a color mask (Fig. 2(b)). Now we apply the operation of logical multiplication to the original image, assign the value of the background pixels to a black color value, and get a segmented plant.

Denoising Segmentation does not always work well (see Fig. 2(c)). Small areas of the background may fall into the range of green values which distorts the binary mask as in Fig. 3(a).

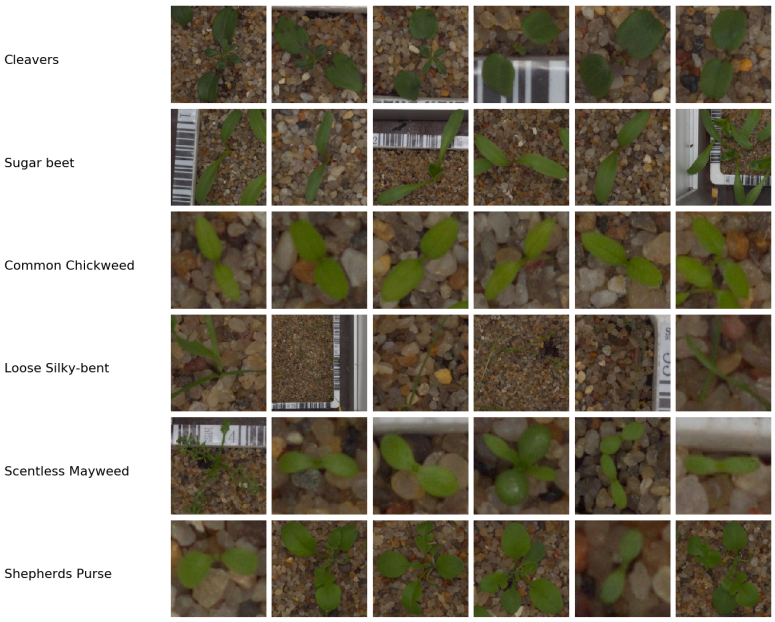
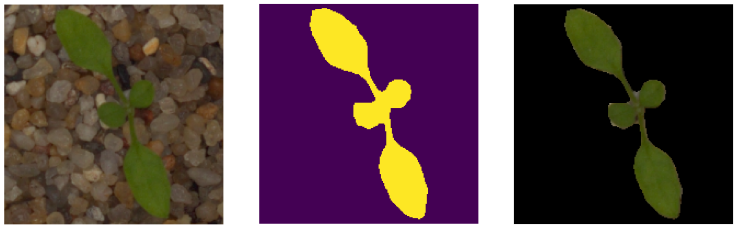


Fig. 1. Data overview



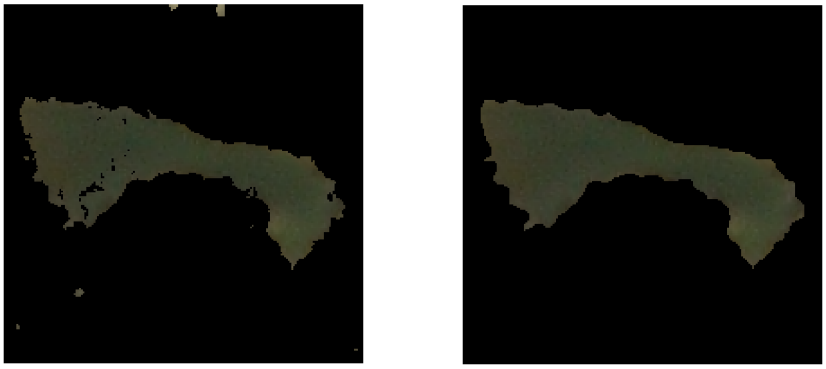
(a) (b) (c)

Fig. 2. (a) Source image; (b) Mask; (c) Segmented image

Such drawbacks can be eliminated by the morphological operations of the nonlinear transformation associated with the shape and structure of an image. The morphology is used to study the interaction of an image with a specific structural element, *the kernel*. The kernel iterates over the entire image and compares with the neighborhood of the pixels after which we apply morphological operations [7].

To improve segmentation, we use the operation of the morphological closure—a combination of the dilatation and erosion operations [6].

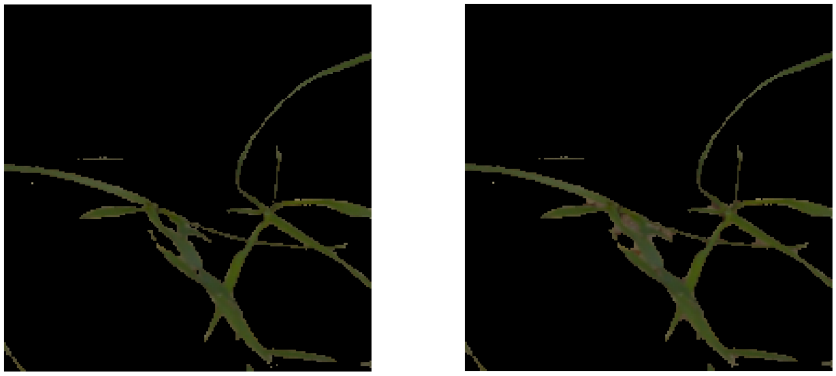
Then we apply the morphological closure operation to the image (Fig. 4(a)) by selecting an elliptical core of 6x6px size and delete the remaining objects



(a) Before morphological closure (b) After morphological closure

Fig. 3. Segmentation improvement example

within an area of less than 160px. The plant on the image (Fig. 4(b)) has no cavities, and the background is cleared of non-plant elements. But the morphological closure does not always improve the segmentation result. Estimate the result of processing an image of the class Loose silky-bent in Fig. 4: the cavities corresponding to the background were restored that does not correspond to the desired result. We restrict ourselves to the removal of objects whose contours limit a small area.



(a) Before morphological closure (b) After morphological closure

Fig. 4. Segmentation degradation example

2.3 Feature selection

The features of images define their content. Consideration of a great number of features helps us to recognize the information better. Image features let the classifier propose the output decision. Another advantage of the approach is that it reduces feature space for a machine learning algorithm. We often need only a part of the information on the image, hence we do not need to process and evaluate all the pixels, which can cause additional computational expenses.

Selecting features is a complicated and convoluted research area itself, the statement is supported by the variety of feature types, and the need of presenting essential properties on an equal basis with the previous assertion.

The goal is to define the set of features describing the dataset in the best way. Supposed features must satisfy the following criteria:

1. The feature space should be low-dimensional
2. The features should not correlate or correlate as little as possible
3. Selected features should represent the content of an image as fully as possible

Now we are going to define the selected features.

2.4 Color features

Overviewing the dataset, we notice that all the plant species are mostly green. Additionally, their images are recorded under specific conditions. We use RGB color model, which stands for red, green, and blue colors, and calculate features described below.

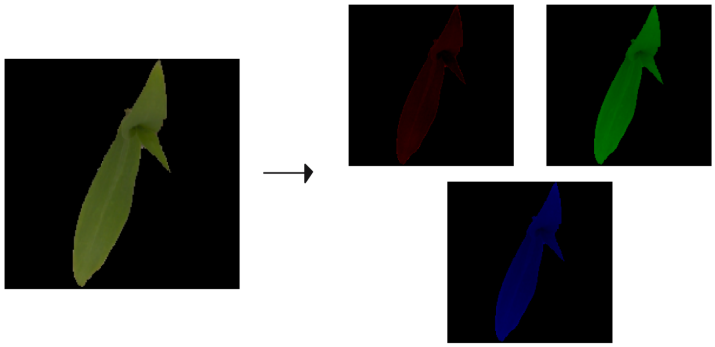


Fig. 5. RGB transformation

Let $\{x^{(k)}\}_{i=1}^{N}$, where $k = 1, 2, 3$ is an index of a channel in the RGB color space, respectively; N is a total number of the image pixels; $x_i^{(k)}$ is an i-th pixel

of the k-th channel. Next, compute the sample mean and standard deviation for each channel:

$$\overline{x^{(k)}} = \frac{1}{N}\sum_{i=1}^{N} x_i^{(k)} \tag{1}$$

$$s^{(k)} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i^{(k)} - \overline{x^{(k)}})^2} \tag{2}$$

2.5 Shape features

A widely-used approach to retrieve shape features is to detect and analyze bounding contours. Here we use the boundary tracing algorithm for the boundary extraction. The designated algorithm [14] is implemented in the OpenCV [2] library for the Python programming language. The studies do not take into account the contours bounding areas below a certain threshold, which is empirically chosen.

Let K be a number of detected bounding contours above the threshold in the further contour-related characteristics.

Total perimeter. For this feature, we count the sum of perimeters of all the areas bounded by contours:

$$P = \sum_{i=1}^{K} p_i, \tag{3}$$

where p_i is an i-th perimeter.

Entire area. It includes all the areas bounded by contours:

$$S = \sum_{i=1}^{K} s_i, \tag{4}$$

where s_i is an i-th area.

Maximal contour area. Here, we analyze the contours bounding maximal areas:

$$S_m = \max s_i,\ i = 1, \ldots, K. \tag{5}$$

where s_i — i-th area

Rectangularity. One of the methods to estimate rectangularity is to plot minimum bounding rectangle. Rectangularity is the ratio of the entire object area to the minimum bounding rectangle area. This feature represents how rectangular an object is:

$$f_{rect} = \frac{S}{S_{MBR}}, \tag{6}$$

where S is the entire area, S_{MBR} is the minimum bounding rectangle area.

Circularity. Another title of this shape factor is the isoperimetric quotient, and it shows how much area per perimeter is bounded:

$$f_{circ} = \frac{4\pi A}{P^2}, \tag{7}$$

where P is an entire perimeter; A is an entire area of all detected elements of a plant.

The correlation matrix of the described features has the form:

	area	largest_area	perimeter	aspect_ratio	circularity	mean_r	mean_g	mean_b	stddev_r	stddev_g	stddev_b	skew_r	skew_g	skew_b
area	1	0.89	0.25	-0.24	-0.36	-0.0072	0.28	-0.31	-0.071	0.096	0.063	-0.11	-0.24	-0.055
largest_area	0.89	1	0.42	-0.19	-0.23	0.084	0.28	-0.27	-0.00094	0.19	0.19	-0.17	-0.22	-0.17
perimeter	0.25	0.42	1	-0.12	0.59	-0.046	0.06	-0.038	0.29	0.36	0.3	-0.046	0.053	-0.14
aspect_ratio	-0.24	-0.19	-0.12	1	0.026	0.057	-0.037	0.11	0.045	-0.016	0.0031	-0.0074	0.048	-0.0021
circularity	-0.36	-0.23	0.59	0.026	1	-0.072	-0.17	0.17	0.31	0.21	0.15	0.023	0.17	-0.056
mean_r	-0.0072	0.084	-0.046	0.057	-0.072	1	0.83	-0.18	-0.009	0.24	0.41	-0.3	-0.32	0.098
mean_g	0.28	0.28	0.06	-0.037	-0.17	0.83	1	-0.28	-0.063	0.31	0.39	-0.22	-0.45	0.064
mean_b	-0.31	-0.27	-0.038	0.11	0.17	-0.18	-0.28	1	0.19	-0.013	-0.25	0.15	0.38	-0.38
stddev_r	-0.071	-0.00094	0.29	0.045	0.31	-0.009	-0.063	0.19	1	0.71	0.55	-0.005	0.39	0.095
stddev_g	0.096	0.19	0.36	-0.016	0.21	0.24	0.31	-0.013	0.71	1	0.58	-0.41	-0.077	-0.049
stddev_b	0.063	0.19	0.3	0.0031	0.15	0.41	0.39	-0.25	0.55	0.58	1	-0.12	-0.022	0.035
skew_r	-0.11	-0.17	-0.046	-0.0074	0.023	-0.3	-0.22	0.15	-0.005	-0.41	-0.12	1	0.55	0.34
skew_g	-0.24	-0.22	0.053	0.048	0.17	-0.32	-0.45	0.38	0.39	-0.077	-0.022	0.55	1	0.14
skew_b	-0.055	-0.17	-0.14	-0.0021	-0.056	0.098	0.064	-0.38	0.095	-0.049	0.035	0.34	0.14	1

Fig. 6. Feature correlation matrix

Based on the data in Fig. 6, we conclude that the most linearly dependent features are the entire area and the largest area. This is not true for all classes due to the predominance of plants bounded by the only one contour. Therefore, the largest area feature is not rejected.

2.6 Classification

The main method for solving this task is the Support Vector Machine (SVM), a binary classification algorithm based on building a separating hyperplane. The

other methods we apply are K-Nearest Neighbors [4], Naive Bayes [11] and Decision Tree [3] classifiers. These algorithms are implemented in the Scikit-learn ([10]) library for the Python programming language.

We will use the Radial Basis Function (RBF) as the kernel function for SVM. The choice is made based on the following advantages. RBF allows to build a hyperplane when the data is not linearly separable.

Data normalization. The SVM algorithm is sensitive to non-normalized data, especially when using the RBF kernel, which is the Euclidian distance itself. In the case when the feature values are at different intervals, a slight difference in one of them can lead to going out of range in second feature values. The solution is to map all the values into one segment. In this task, we will choose $[0, 1]$.

3 Results

3.1 Metric

Results of classification are evaluated by the micro-averaged F-score. Given the positive and negative rates for each class, the resulting score is computed as follows:

$$Precision_{micro} = \frac{\sum_{k \in C} TP_k}{\sum_{k \in C} TP_k + FP_k}, \quad Recall_{micro} = \frac{\sum_{k \in C} TP_k}{\sum_{k \in C} TP_k + FN_k} \tag{8}$$

$$F_{micro} = \frac{2 * Precision_{micro} * Recall_{micro}}{Precision_{micro} + Recall_{micro}}, \tag{9}$$

where C is a set of the plant classes

The choice of such a metric is supported by the fact that classes are imbalanced. In this case, the influence of classes decreases due to averaging by classification characteristics, not by F-scores.

The classificator result is shown in Table 1. The worst classification we received at Black-grass class. .

3.2 Models comparison

The choice of the SVM is justified by better results in comparison with other classical methods of machine learning. Table 2 shows micro-averaged F-scores for Naive Bayes, k-nearest neighbours and Decision tree classifiers. The Naive Bayes showed the worst results due to the fact that he is sensitive to the correlation between features. The decision tree worked out significantly worse than SVM, because we used the RBF kernel in SVM. Since the k-nearest neighbours

Table 1. Detailed metrics for SVM classificator

Type	Precision	Recall	F-score
Sugar beet	0.901	0.936	0.918
Fat Hen	0.877	0.909	0.893
Scentless Mayweed	0.851	0.905	0.878
Charlock	0.947	0.934	0.940
Small-flowered Cranesbill	0.963	0.991	0.977
Maize	0.953	0.891	0.921
Shepherds Purse	0.833	0.714	0.769
Common Wheat	0.800	0.889	0.842
Common Chickweed	0.962	0.962	0.962
Cleavers	0.885	0.852	0.868
Loose Silky-bent	0.828	0.888	0.857
Black-grass	0.757	0.528	0.622
Micro-averaged F-score		0.885	

algorithm is insensitive to nonlinear data, the result is as high as SVM. These methods are implemented in Scikit-learn ([10]) library. All the experiments are conducted 100 times each; on shuffled data, these metrics are obtained by testing on a validation sample and averaged.

Table 2. Metrics for used classificators

Method	Micro-averaged F-score
naiveBayes	0.72
kNN	0.84
decisionTree	0.73
SVM	**0.885**

4 Conclusion

In this paper, we applied the feature-based method in the image classification task. The constructed algorithm is implemented and evaluated on the real plant dataset containing images of 12 different types of seedlings. We selected and extracted features using computer vision algorithms. As it is shown in Table 2, the best performance is reached with Support Vector Machines algorithm. The detailed result for the best method is shown in Table 1. Some of the classes are

not recognized well due to minor differences between some types of proposed plants. The future work is aimed to improve segmentation output and to try other types of image features.

References

1. Bellman, R.: Dynamic Programming. Princeton University Press, Princeton, NJ, USA, 1 edn. (1957)
2. Bradski, G.: The opencv library. Dr. Dobb's Journal of Software Tools (2000)
3. Breiman, L., Friedman, J., Stone, C., Olshen, R.: Classification and Regression Trees. The Wadsworth and Brooks-Cole statistics-probability series, Taylor & Francis (1984)
4. Cunningham, P., Delany, S.: k-nearest neighbour classifiers. Mult Classif Syst (2007)
5. Davis, P.J.: Interpolation and Approximation. Dover Publications, New York, USA (1963)
6. Efford, N.: Digital Image Processing: A Practical Introduction Using JavaTM. Pearson Education (2000)
7. Friel, J.J.: Practical Guide to Image Analysis. ASM International (2000)
8. Giselsson, T.M., Jørgensen, R.N., Jensen, P.K., Dyrmann, M., Midtiby, H.S.: A public image database for benchmark of plant seedling classification algorithms (2017)
9. Pechenizkiy, M., Puuronen, S., Tsymbal, A.: Feature extraction for classification in knowledge discovery systems (2003)
10. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E.: Scikit-learn: Machine learning in python. J. Mach. Learn. Res. (2011)
11. Rish, I.: An empirical study of the naïve bayes classifier. IJCAI 2001 Work Empir Methods Artif Intell **3** (2001)
12. Shi, L., Wan, Y., Gao, X., Wang, M.: Feature selection for object-based classification of high-resolution remote sensing images based on the combination of a genetic algorithm and tabu search. Computational Intelligence and Neuroscience (2018). https://doi.org/10.1155/2018/6595792
13. Smith, A.: Color gamut transform pairs. ACM Siggraph Computer Graphics **12** (1978). https://doi.org/10.1145/800248.807361
14. Suzuki, S., Abe, K.: Topological structural analysis of digitized binary images by border following. Computer Vision, Graphics, and Image Processing (1985). https://doi.org/10.1016/0734-189X(85)90016-7, https://doi.org/10.1016/0734-189X(85)90016-7
15. Yang, M., Kpalma, K., Ronsin, J.: A survey of shape feature extraction techniques (2008)