

A machine learning approach for grain crop's seed classification in purifying separation

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Abstract. The paper presents a study of the machine learning ability to classify seeds of a grain crop in order to improve purification processing. The main seed features that are hard to separate with mechanical methods are resolved with the use of a machine learning approach. A special training image set was retrieved in order to check if the stated approach is reasonable to use. A set of tests is provided to show the effectiveness of the machine learning for the stated task. The ability to improve the approach with deep learning in further research is described.

1. Introduction

In the modern agricultural production cycle, the purification of seed material becomes a significant part and needs to be well developed to cover all society needs in this area. The traditional mechanical approaches to purify the material are now complemented with the power of computing facilities. In order to enhance the efficiency of this production stage, different methods are combined in one active block, usually applied in final iterations of the purification line.

Nowadays, the trend methods including an object detection and a classification via computer vision (CV) are neatly applied to tackle most problems of recognition and classification. The CV technologies usually increase the efficiency of the whole system and even bring it to the new operating level [1], but in case of seed classification and real task application, the studies are not held profoundly. However, such processing optimization is promising from different points of view [2,3,4].

This paper presents an investigation and research of an image processing approach that can provide efficient seed classification accuracy and recognition speed for the grain crops purification line.

2. Materials and methods

The seeds of five kinds were used as a material in image caption and further processing. These five kinds were chosen as a mass-market and most sufficient for the Russian agriculture sphere: wheat, rapeseed, phacelia, flax, white mustard seeds. Each kind represents a group to classify. According to several free public image training datasets (The University of Texas, Computer science department's datasets: <http://www.cs.utexas.edu/~grauman/courses/spring2008/datasets.htm>; The University of Edinburgh, the School of Informatics' datasets: <http://homepages.inf.ed.ac.uk/rbf/CVonline/Imagedbase.htm>; the University of Illinois, datasets for Computer Vision Research: http://www-cvr.ai.uiuc.edu/ponce_grp/data/) there are no suitable seed image databases for the stated task available for the experiments. Thus, real seeds were used to fill an image dataset for experiments. A cheap equipment presented with a Canon digital camera, a smartphone camera and a stripe of white and RGB LED light along with a small amount of seeds was



used to provide minimum cost experimental data and estimates the further research necessity. The experimental dataset was filled with captured images of these five seed kinds. Each kind enumerates about one hundred of images, thus the whole set is more than five hundred images in total.

In order to conduct research of an object recognition and classification for the stated task the modern computer vision technologies and rapidly developed method such as machine learning were used [5, 6]. The method is available in the Matlab toolbox (the version used is R2016a) which is based on common feature extraction techniques include Histogram of Oriented Gradients (HOG), Speeded Up Robust Features (SURF), Local Binary Patterns (LBP), Haar wavelets, and color histograms [7,8]. A convolutional neural network (CNN) classifier was established as a way to improve the classifying accuracy of the approach [9,10].

3. The study of the ability to classify seeds culture

Reasoning from theoretical premises, object classification based on images can be done with different approaches, but the main appropriate one for the stated task is computer vision. The CV is a relatively new technology that provides cutting edge methods applications which deal with real tasks. One of the most significant requirements is the processing speed. Regarding the task features consisting in that seeds will fall down in front of the camera, the method should provide fast image capture and object class recognition. The real production problem is to find out what type of a grain crop is detected to separate it from the main seed flow. Thus, the second key feature is accuracy. It is needed to provide high level accuracy in classification to minimize the grain crop recognition error and reduce the number of separating iterations to reach the desirably clean product.

The stated problem and its features are mostly covered by the traditional machine learning approach [11]. It is based on image feature extraction, descriptors retrieval, clustering and finished with vocabulary of visual words (Figure 1).

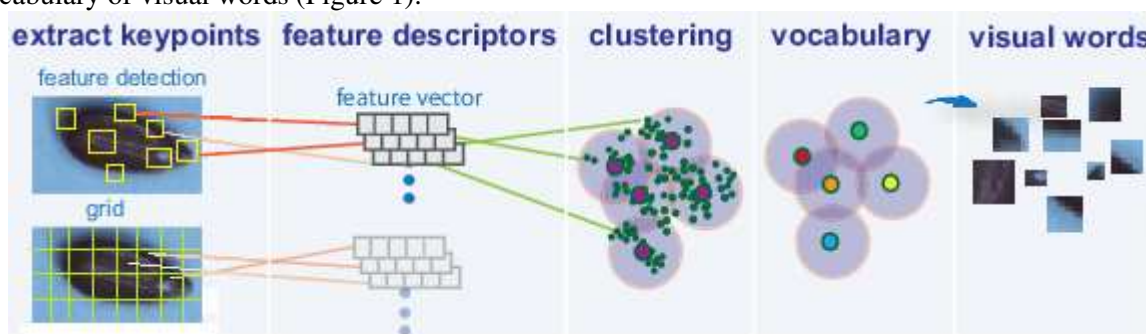


Figure 1. An overview of a seed image bag of features and visual words extraction.

This approach does not require a huge number of training images to train the classifier, as well as the speed is fast enough to train a new classifier in minutes. Applying this classifier, the result is provided with a set of values that shows how close is the object to each class (Figure). The most value indicates the most predictable class of the object.

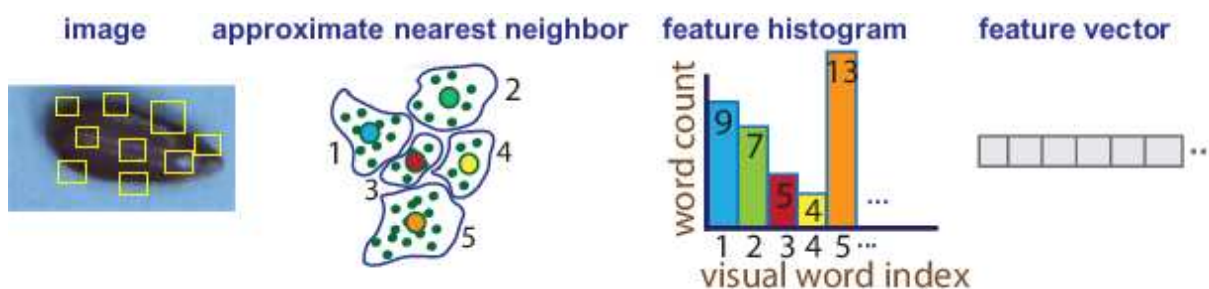


Figure 2. An overview of the traditional machine learning classification process of the seed image.

Figure 3 shows photos of real seeds that were used to fill a small training dataset. The small dataset

will show the efficiency of the method and will provide the minimum experimental base without huge investments. This approach was chosen in case of risks prevention, because the chosen method can result in low accuracy, and the artificial environment along with equipment needed for the further research is expensive.



Figure 3. A seed image example from the training dataset: a – wheat; b – rapeseed; c – phacelia; d – flaxseed; e – white mustard seed.

As is seen from Figure 3, seeds have different visual features: shape, color, surface, glance. These parameters are hardly recognisable with traditional mechanical methods, and separation is made basically in terms of the size and weight. Applying a camera with fast computer processing with the pre-trained classifier will cover the missing parameters of mechanical sorting and will provide the better sorting accuracy [2,4].

Meanwhile the traditional machine learning approach is not the last stage in seed classification and separation process improvement. A new approach based on neural networks becomes widely spread due to its efficiency [12]. Figure 4 shows the difference between traditional and deep learning. The key feature of the second method is that it provides more accuracy, but need to be trained on the basis of a much bigger and variable image set in comparison with the first one. Deep learning implies having thousands of images for each class to be trained. The training process of deep learning is performance consuming and can take the time of a week for real tasks [13,14]. Thus deep learning is seen as a resource of efficient improvement that theoretically will provide better results and will be used if the traditional machine learning will work for the stated problem. In comparison, the deep learning approach evaluated by MATLAB yields up to 95% classification accuracy when traditional learning yields only about 75% [7, 13].

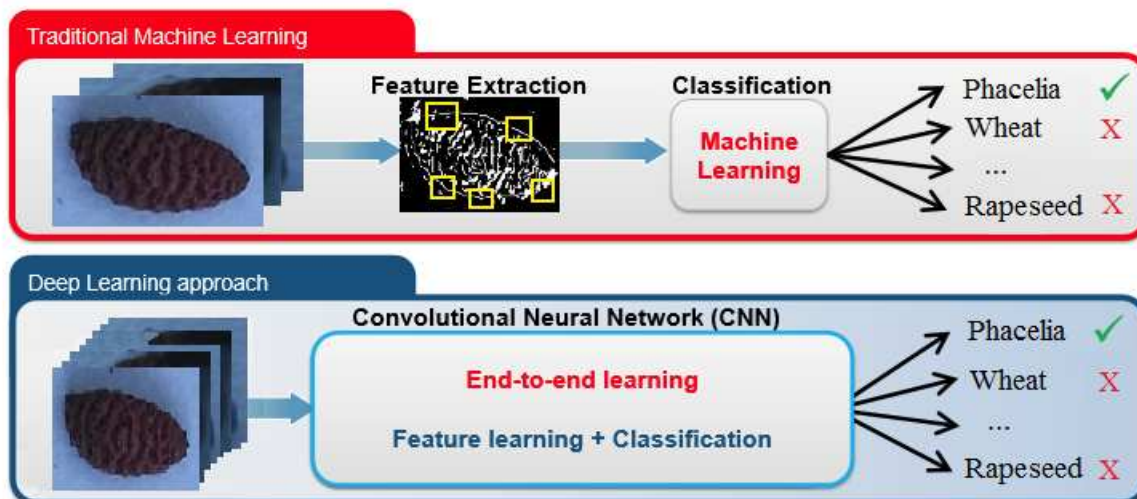


Figure 4. The diagram of traditional machine learning and the deep learning approach.

4. Results

The experiments of seed classifier training were conducted using MATLAB with the Computer Vision toolbox on the basis of the test collection of seed images. The first test set provided results of the usage of different vocabulary sizes. The MATLAB default value for this size is 500 and the test range contains values from 10 to 30000. The procedure consisted of the following steps:

- Load test seed images dataset.

- Randomly divide the dataset into training and test parts with a 0.3/0.7 ratio.
- Extract a bag of features with the n^{th} test vocabulary size.
- Train the image category classifier on the basis of the training part of the dataset.
- Evaluate accuracy on the test part of the dataset.

The classification accuracy dependency on the vocabulary size is shown in Table 1. It is obvious that values smaller than the default value provide low accuracy. At the same time, increasing the vocabulary size requires much more time for training and results in the 75%–85% range. The vocabulary size of 5000 words was chosen for further tests.

Table 1. Dependence of the vocabulary size on average classification accuracy

Training/Evaluating ratio	Vocabulary size, number of words	Number of extracted features	K-Means clustering, number of iterations	Average time for iteration, s	Average accuracy, %
0.3/0.7	30000	169970	39	6.66	85.02
0.3/0.7	15000	167775	28	4.19	79.45
0.3/0.7	10000	183410	28	2.92	86.31
0.3/0.7	5000	138210	31	1.45	84.04
0.3/0.7	2000	119295	33	0.87	76.57
0.3/0.7	1000	134370	18	0.84	76.30
0.3/0.7	500	115330	30	0.68	75.97
0.3/0.7	100	168335	30	0.88	63.10
0.3/0.7	50	200640	34	1.04	61.90
0.3/0.7	10	165790	40	0.61	47.01

The second set of tests was dedicated to different training/evaluating ratios. The procedure contained the same spets as stated above did, but the vocabulary size for the test is constant and the training/evaluating ratio is variable. Table 2 shows the results of the tests. The bigger is the training part, the better the result is. The test also proves that the classifier can be trained well with a small dataset, but the training part smaller than a third of images number is not enough to provide the accuracy. However, it is not reasonable to use only 10% of images for evaluating because of high chance not to cover all cases. Considering this, the middle values are suitable for the traing/evaluating ratio.

Table 2. Dependence of the training/evaluating ratio on average classification accuracy

Training/Evaluating ratio	Vocabulary size, number of words	Number of extracted features	K-Means clustering, number of iterations	Average time for iteration, s	Average accuracy, %
0.1/0.9	5000	56510	39	0.92	67.88
0.2/0.8	5000	123150	44	1.41	74.84
0.3/0.7	5000	181345	32	1.97	85.00
0.4/0.6	5000	243730	27	2.41	84.44
0.5/0.5	5000	336960	37	3.27	90.75
0.6/0.4	5000	316145	27	2.93	93.15
0.7/0.3	5000	396015	41	3.69	95.88
0.8/0.2	5000	406640	33	3.68	96.49
0.9/0.1	5000	454575	43	4.07	100.00

The last set of tests was aimed at influencing randomization of the training part. Average classification accuracy for 10 test trainings with training/evaluating ratio 0.3/0.7 and a vocabulary size of 5000 words is 82.56%. This value is even better than 75% – the theoretical estimation of MATLAB for traditional machine learning.

5. Conclusion

After conducted studies of seed culture classification with computer vision, it is possible to conclude that the computer vision technologies are appropriate for improving the process of seed classification in order to provide better grain crop purification processing. The machine learning approach is recommended as a flexible and accurate way for fast classifier training.

The experiment showed high results on the basis of visibly different categories and proved that it can be used to classify color, shape, surface and glance – features that was previously hard to differentiate without computer vision.

According to close theoretical and experimental results of traditional machine learning classifying accuracy, it can be considered as appropriate for the stated seed classification task. The theoretical estimation of the deep learning accuracy provides the field of improving the classification ability of the method. It will need more training images and better equipment, but the result now is seen to be good enough to try. The high frame rate camera with good lenses and light can provide the necessary image set retrieved in close-to-real working conditions. Other categories of grain crop seeds such as rice, oat and corn are recommended to extend the variety of training images especially for deep learning, which supports adding new categories without losing previously trained results.

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