Toward Objective Variety Testing Score Based on Computer Vision and Unsupervised Machine Learning: Application to Apple Shape

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Abstract: While precision agriculture or plant phenotyping are very actively moving toward numerical protocols for objective and fast automated measurements, plant variety testing is still very largely guided by manual practices based on visual scoring. Indeed, variety testing is regulated by definite protocols based on visual observation of sketches provided in official catalogs. In this article, we investigated the possibility to shortcut the human visual inspection of these sketches and base the scoring of plant varieties on computer vision similarity of the official sketches with the plants to be inspected. A generic protocol for such a computer vision based approach is proposed and illustrated on apple shape classification. The proposed unsupervised algorithm is demonstrated to be of high value by comparison with classical supervised and self supervised machine and deep learning if some rescaling of the sketches is performed.

1 INTRODUCTION

Plant variety testing refers to the activity of assessing new varieties of plants before registering them in an official authorized catalog. The test can assess characteristics such as appearance, resistance to various stresses and agronomical value. So far variety testing is mostly based on human visual inspection. For scoring of key characteristics, experts follow guidelines in the form of either written instructions or visual reference sketches. Such guidelines are usually delivered in a catalog by an official variety testing organism, such as *The International Union for the Protection of New Varieties of Plants* (UPOV). Trait descriptors are also scored by breeders and germplasm curators, who follow in-house or published/recommended guidelines. Two limitations of manual assessment by experts are that the rating is non-objective and that the process is slow and time-consuming. The objective of this article is to propose a fast and objective generic protocol adapted to the specific requirement of variety testing with the help of computer vision.

Computer vision is now widely used in plant phenotyping and agriculture (Mahlein, 2016; Li et al., 2020; Dhanya et al., 2022) and especially for fruit phenotyping (Bhargava and Bansal, 2021). Computer vision has been only recently explored in the domain of variety testing (Couasnet et al., 2021; El Abidine et al., 2020; Zine-El-Abidine et al., 2021; Garbouge et al., 2021b; Garbouge et al., 2021a; Koklu et al., 2021; Meng et al., 2022; Cao et al., 2022). This article is a new contribution in this recent application domain of computer vision to variety testing.

One can distinguish two approaches in computer vision (Szeliski, 2022). The traditional approach is the model-based approach where the characteristics of the objects to be analyzed in the scene are translated into geometrical shapes. Features, i.e. set of numbers, are then computed on these geometrical shapes and the computer takes decision in this feature space. The current leading approach is the data-driven approach where the features space and the decision making are built, without the help of a mathematical expert to translate shape into features, in a supervised manner based on training data set (part of the data on which the expect output of the model, i.e. ground truth, is manually established) to produce a model that will then be used for inference on unseen data.

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Coupling computer vision with data-driven supervised machine learning techniques has been proven to be successful for many phenotyping tasks (Benos et al., 2021; Li et al., 2020; Pathan et al., 2020). However, computer vision models produced via supervised machine learning depend on the training data set. Consequently, there are some constraints on the training data set to ensure a good generalization on the unseen data set. First, the training data set has to be representative of the unseen data to be tested. Second, the size of the training data set has to be large enough to fit with good generalization properties the parameters to be adapted in the models. When using Deep learning, the most powerful and common tools in data driven approach, the typical minimal size of the training data set is some few thousands or instances at least. These basics of supervised machine learning clearly indicate that this approach is not suitable to mimic the current protocol for variety testing. Indeed, in variety testing experts establish their ratings in reference to the visual comparison between a very small set of sketches (typically some units) and the inspected real plants. These sketches cannot constitute a large enough training set. Also, since the experts can disagree on their ratings due to subjective interpretations of the official sketches, supervised machine learning using ground truth provided by an expert may embed some bias to their inference models and therefore not be representative of the unseen data to be tested.

Supervised machine learning appears not suitable for variety testing based. In this work, we investigate the possibility to directly use reference sketches in an official catalog for quantitative matching with images of plants to be assessed (see Fig. 4). We test this approach, which is novel in the context of variety testing, on the problem of apple shape assessment. The closest related problem in computer vision is sketch-based image retrieval (SBIR), where the objective is the retrieval of related images from a data base given a sketch query (see (Zhang et al., 2019) for a recent review). The SBIR method combines information from both datasets (sketches and RGB images) for a high accuracy image retrieval. Rather than image retrieval, we target classification of RGB images of apples by quantitatively matching them with catalog sketches.

As another field of related work, shape-based classification and grading of fruits based on supervised machine learning has been widely studied in the literature (Ishikawa et al., 2018; Jana and Parekh, 2017; Kheiralipour and Pormah, 2017; Hu et al., 2018; Ireri et al., 2019; Li et al., 2019). By contrast, while we use classical shape features to characterize the shape of apples, we do not promote a supervised machine learning techniques here. To the best of our knowledge, there exists no previous work for development of a sketch-based classification tool in the context of variety testing.

The article is structured in the following way. We first present the material and methods used for the apple use case chosen to illustrate our a sketch-based classification tool. For fair comparison we will naturally compare our approach either in terms of performance and energy consumption with some of the state-of-the-art supervised or self-supervised deep learning methods. We demonstrate and discuss the domain of superiority of our approach and its generic interest for other use cases in variety testing conclude.

2 MATERIALS AND METHODS

2.1 Reference Sketches

The apple shape classification tool currently follows the UPOV rules. In this variety testing framework, experts inspect cut apple shapes by comparing them to the reference sketches in the official variety testing catalog (see Fig. 1). Three main classes are used to designate the shape of apples: *Flat*, *Globose* and *Oval*. For each category, there are sub-categories such as *Flat-Globose*, *Oblong* and *Ellipsoid*. In this study, we target classification of apple images into three broad categories: *Flat*, *Globose* and *Oval*.

2.2 Data Set

The image acquisition procedure is shown in Fig. 2. As image acquisition procedure, apples from the Refpop population (Jung et al., 2020)) are cut along their medial axis, placed on their flat, freshly cut side in groups of 6 on an HP Scanjet Pro 4500 fn1 with maximum resolution of 1200 x 1200 dpi. Since the contrast between the apples and the background is strong, we used simple thresholding on the brightness channel of HSB color space to segment the apples from the background. The bounding box of each individual apple is obtained through connected component analysis. A simple edge detection via Sobel filter is applied to produce a binary image highlighting the boundaries of the apples (see Fig. (4)).

Overall, 1821 images were acquired and classified independently by two experts. Figure 3 shows the distribution of the classes (*Flat*, *Globose* and *Oval*) corresponding to the annotations of the two experts. Three sets of class labels resulted from this annotation. The class labels provided by expert 1, by expert 2 and a subset labeled in agreement by both ex-

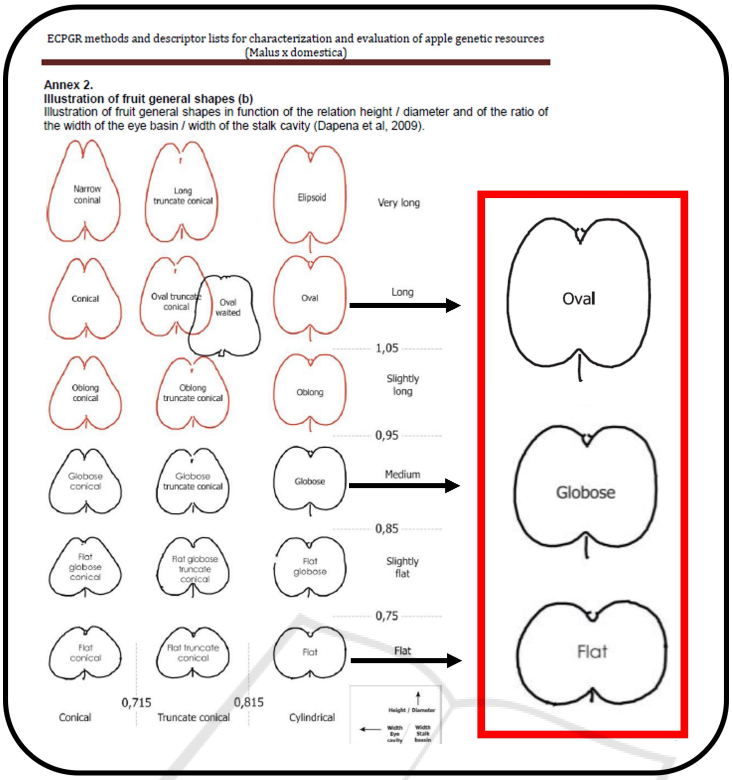

Figure 1: Reproduced and modified view of the ECPGR catalog. Apple shape sketches in the catalog of variety testing. The classes considered in this work are highlighted in the red rectangle.

Figure 2: Acquisition device: HP Scanjet Pro 4500 fn1.

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perts (600 images) were kept. This quantifies the inter-variability between expert and the current consequences of subjective rating. This also shows the intrinsic difficulty of the visual tasks raised to experts in variety testing where experts only agree in 30% of the cases.

2.3 Shape Descriptors

In this article, since our aim is not to provide new features to characterize apple shape but rather to investigate the possibility to use the reference sketches for apple shape classification, we used some existing shape descriptors (Ishikawa et al., 2018; Ghazal et al., 2021). We used chain-code histogram, elliptical Fourier descriptors (Kuhl and Giardina, 1982) and Frechet's Ratio with the following hyperparameters. The connectivity for the chain-code was take to 8. The 10 first harmonics of elliptical Fourier descriptors were kept. All features were normalized to 1 to allow the use of Euclidean distance in the produced feature space.

2.4 Experiments

We evaluated two approaches for apple classification: i) reference-based classification approach and ii-) three model-based classification approaches, one based on support vector machine (SVM), one based on supervised deep neural network and one based on self-supervised deep neural network. The details are provided in the following subsections.

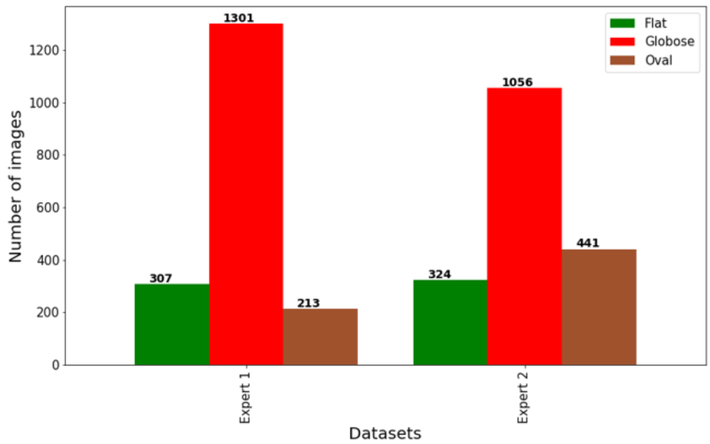

Figure 3: Histogram of the distribution of classes (*Flat*, *Globose* and *Oval*) assigned by experts.

2.4.1 Reference-Based Classification Approach

In this experiment, we mimic the way variety testing experts use catalogs. We perform a multi-class classification by computing the Euclidean distance between features of cut apple query image and features from a reference instance of each class: one for *Flat*, one for *Globose* and one for *Oval*. A visual abstract of the pipeline is given in Fig. (4). Three types of references were tested i) the original sketches from the official catalog of ECPGR, ii) the contours from real apples each representing a class, iii) The ECPGR sketches rescaled.

First, we considered the original sketches from the official catalog of ECPGR. As the second option, instead of the sketches provided in a catalog, we considered the contours of representative apples as reference shapes. The representative apples are chosen from the dataset of real apple images. For each class, the apple with the aspects ratio closest to the class average is selected as the class representative. As the third option, we modified ECPGR sketches such that the aspect ratio of each reference sketch becomes equal to the corresponding class average. This operation bridges the gap between the aspect ratios of the sketches and the distribution of the aspect ratio of the apple variety to be tested.

The average aspect ratio was computed in the following unsupervised way. We assigned the centroids of each cluster as the class average aspect ratio to the corresponding class knowing the ordinal relation between classes. This sorting was obviously not perfect (otherwise the task would have been done).

2.4.2 Alternative Classification Approaches

In this approach, we do not follow the ECPGR catalog and rather adopt supervised machine learning techniques. Three models are trained to classify the shape of images based on a training set composed of annotated RGB images. Since our goal is not to claim optimal performances but rather to provide a comparison with our proposed reference-based approach, we selected a basic machine learning model (an SVM with a linear kernel) and two deep learning algorithms including supervised (Kamilaris and Prenafeta-Boldú, 2018; Koirala et al., 2019) and self-supervised deep learning (Güldenring and Nalpantidis, 2021). The well-known VGG16 (Simonyan and Zisserman, 2014) and SimSiam (Chen and He, 2021) models have been implemented for supervised and self-supervised deep learning models. To quantify the sensitivity to the choice of the data reserved for the training, multiple runs of the classification experiment were conducted for various values of the train-test split of the data set and 10-fold cross-validation. The average value and standard deviation of the performances of classification were recorded. To quantify the inter-variability between annotating experts, the experiment was repeated with labels provided by separated labels provided by the two experts and with the curated data set containing apples with agreed labels only.

2.4.3 Metric

All the classification experiments were evaluated using the accuracy metric

$$ACC = \frac{TP+TN}{TP+TN+FP+FN}\,. \tag{1}$$

To rely on this metric, the classes *Flat*, *Globose* and *Oval*, on both experts' annotated datasets and cured dataset were balanced with 200 images for each class.

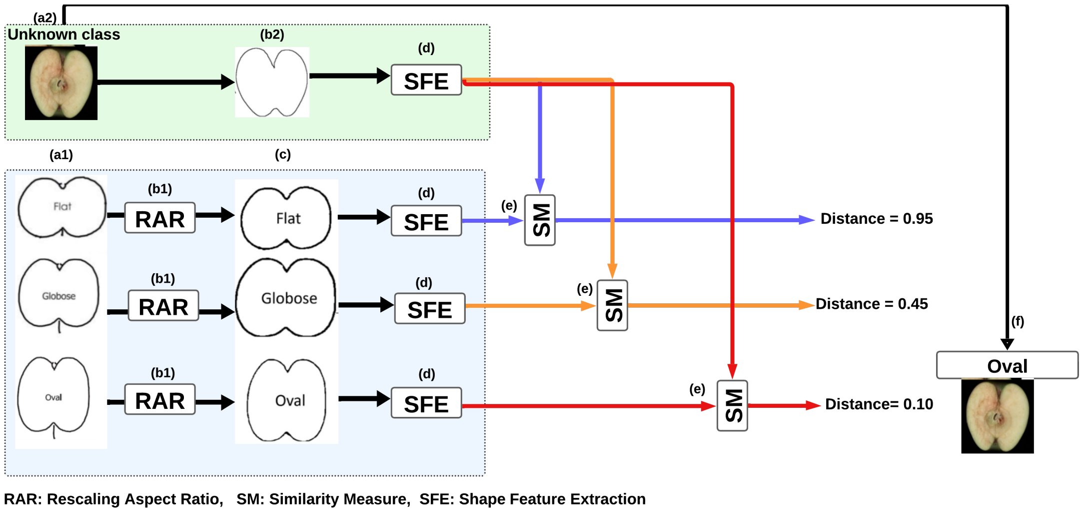

Figure 4: Illustrative pipeline for the Reference-based classification approach: (a1): reference sketches Dataset, (a2): an apple RGB image to be classified. (b1): rescaling of the aspect ratio of sketches for each class. (b2): edge detection. (c) rescaled sketches. (d): shape features extraction. (e): similarity measure. (f): classification results; apple RGB image classified based on the minila distance.

3 RESULTS

3.1 Reference-Based Classification Approach

Table 1 provides quantitative evaluation of reference-based approach results. One can observe low accuracy when the sketches from the ECPGR catalog are used as reference. A noticeable improvement of 9 to 13 % of accuracy is brought when these reference sketches are rescaled. The best performance is obtained when the class representatives are selected as a reference. However, it is to be noticed that the gain of performance is only of a 2 to 4 % by comparison with the unsupervised rescaling of the official sketches. The performance culminates at 77% of accuracy when the data are curated. We reproduced the experiment after withdrawing the intermediate class *Globose*. Results given in Table 2 show similar trends as in Table 1 but with much higher accuracy around 95%. We still observe a gain of 2 to 3% after rescaling the reference sketches of the ECPGR catalog with our proposed approach.

Table 1: Measuring accuracy (*ACC*) of reference-based approach on expert 1 (E1), expert 2 (R2) and curated data (CD), to all types of sketches. Ref stands for reference sketch, Classrep for class representatives sketches and Rescaled for rescaled reference sketches.

Sketches	% ACC_{E1}	% ACC_{E2}	% ACC_{CD}
Ref	58%	55%	60%
Classrep	69%	67%	77%
Rescaled	67%	63%	73%

Table 2: Same as in Table 1 but with only two classes *Flat* and *Oval*.

Sketches	% ACC_{E1}	% ACC_{E2}	% ACC_{CD}
Ref	94%	90%	95%
Classrep	97%	96%	98%
Rescaled	97%	95%	97%

3.1.1 Comparison with Alternative Approaches

Figures 5 shows the performance of the three model-based approaches as a function of the ratio of the size of the test set to the size of the training set. As trivially expected, the performances drop progressively with increasing standard deviation when the amount of data in the training data set reduces. The plateau of performance of the SVM-based method for a low test/training ratio is around 93% for the curated data sets but drops to around 43% with a huge standard deviation of 14% when only one instance is kept. The same behavior could also be seen in the performance curved yield by the deep learning and self-supervised learning approaches. The big gap (around 10% to 20%) in terms of accuracy between the SVM-based approached and supervised Deep learning and self-supervised learning approaches shows that Deep learning and self-supervised learning approaches are more data-dependent than machine learning approaches based on handcrafted-features.

These results should be compared with the reference-based classification approach explained in the previous subsection, where only one image per class was used. It also has to be mentioned that deep learning and self-supervised learning approaches have a high computational cost which affects the environment and global warming. We estimate the amount of carbon dioxide (CO2) produced by our computing resources used to execute these two methods (Schmidt et al., 2021). Our estimation showed that these computations consumed around 69 kWh, which equaled about 27 kg (59.5 pounds) of CO2 emissions.

The results of predictions on test set of curated data, using the same model-based approaches and reference-based approach toward reference sketches, centers representatives and rescaled reference sketches, are presented in Fig. 5. It is important here to recall that the reference-based approach is purely unsupervised and therefore fully automatic in the case of testing of a new variety while the model-based approach require labor-intensive annotation of the newly introduced data set.

The performance of the reference-based classification is found to be stable with the amount of data used to compute the rescaling aspect ratio and outperforms the SVM-based approach when less than 30% of the data sets are not annotated. This experiment was carried out again while withdrawing the intermediate *Globose* class with similar results shown in Fig. 6. The difference of plateau of performance between the SVM-based approach and the reference-based approach vanishes, and there is here no clear advantage in annotating the images to train a model. The current approach based on sketches can directly be automated with the unsupervised approach proposed in this work.

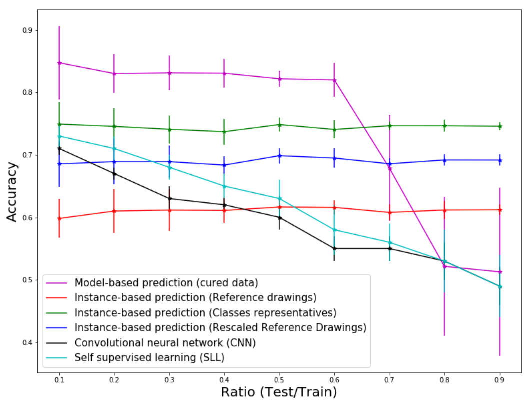

Figure 5: Prediction curves of test set of curated data via model-based classification, CNN and SSL and reference-based classification using reference sketches, centers representatives and rescaled reference sketches, after training on curated dataset.

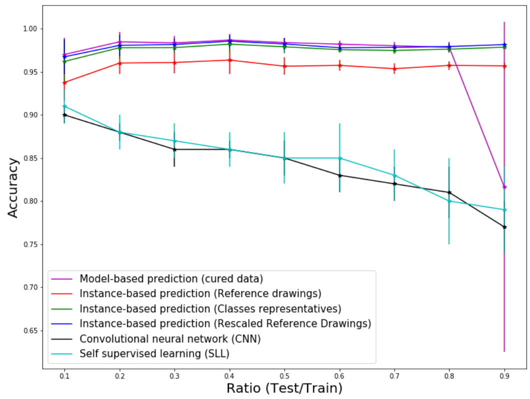

Figure 6: Same as in Fig. 5 with only two classes *Flat* and *Oval*.

4 DISCUSSION

As illustrated in Fig. (7), variety testing catalogs may differ from one country to another, as well as between germplasm curators and breeders, or the sketches of reference may evolve. This situation may cause difficulty of comparison of the results over time or even communication problems between countries not sharing the same references. The instance-based approach described in this article may actually serve to decipher this Tour of Babel problem. As shown in Table 3, we investigated the possibility of automatic translation of one catalog to another. To this purpose, we provided the nearest reference sketches to a query reference sketch from a different catalog.

In Table 3, some catalogs categories are found to be perfectly matching with each others. In other cases the designation used in one catalog does not match with the designation of another catalog. This shape-based translation based on pure objective features enables to overcome the semantic gap that the multiplicity of catalogs may cause. Consequently, our approach may not only be used to provide an objective tool conforming the current variety testing practices, it can also be used when judgements based on different visual references need to be shared. It is here again important to stress that this translation from one catalog of reference to another, would not be directly accessible with supervised machine learning. Indeed this would require to train models with annotation provided by experts using different catalogs. Then it would require to compare this subjective rating result on testing data. By contrast with the unsupervised instance-based model proposed in this article, translation from one catalog to another is almost instantaneous since only the objective similarity between reference sketches need to be computed.

Table 3: Translation between variety testing catalogs. Each line provides K nearest neighbors (K = 6) in the Upov Catalog of query sketches from ECPRG Catalog. The first column gives the query sketches.

ECPGR Catalog			**Upov Catalog**			
Flat	*Flat*	*Oblate*	*Globose-Canonical*	*Ellipsoid*	*Oblong*	*Globose*
Globose	*Globose*	*Globose-Canonical*	*Ellipsoid*	*Oblong*	*Oblate*	*Flat*
Oval	*Globose*	*Ellipsoid*	*Oblong*	*Globose-Canonical*	*Oblate*	*Flat*
Ellipsoid	*Oblong*	*Ellipsoid*	*Globose-Canonical*	*Globose*	*Oblate*	*Flat*
Flat-Globose	*Oblate*	*Flat*	*Ellipsoid*	*Globose-Canonical*	*Oblong*	*Globose*
Oblong	*Globose*	*Oblong*	*Globose-Canonical*	*Oblate*	*Ellipsoid*	*Flat*

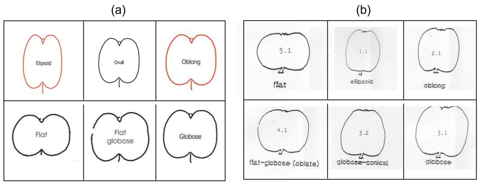

Figure 7: Two different variety testing catalogs. (a): Catalog delivered by The European Malus GERMPLASM Workshop (ECPGR 2009). (b): Catalog delivered by UPOV (2006).

5 CONCLUSION

In this article, we have demonstrated the possibility of using reference sketches in a variety testing catalog, to help the transition from pure manual inspection toward automated computational practices. The sketches can serve as references for quantitative matching to classify images of plant instances. Rescaling of the aspect ratio of the reference sketches was shown to be helpful to boost the performances of classification. Reference-based approach was shown to be better suited in variety testing as compared to supervised machine learning approaches since the later requires intensive manual annotation and therefore brings no gain of efficiency to the current practice of manual inspection. This work opens several perspectives. Although the proposed methodology was illustrated on apple shape evaluation in variety testing, it could be extended to any of variety testing traits associated with reference sketches of the official catalogs. Some sketches in variety testing correspond to 3D rendered views. In this case the correspondence with the 2D images would not be as direct as in this article. It would require to first acquire a set of images in 3D view and then find the best match with the pose of the reference sketch in the catalogue. Concerning apple, we followed the official protocol and operated with freshly cut apples. It would be interesting to reproduce the experiment with uncut apples to find if the variety testing protocol could be adapted uncut apples for faster and non destructive characterization. On the side of artificial intelligence, we demonstrated the limits of state of the art convolutional neural network either in supervised or self-supervised learning for limited data set size by comparison with our approach. It would be interesting to extend the comparison with the recently introduced foundation models which are expected to perform better with few or even zero -shot learning.

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REFERENCES

Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., and Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. *Sensors*, 21(11):3758.

Bhargava, A. and Bansal, A. (2021). Fruits and vegetables quality evaluation using computer vision: A review. *Journal of King Saud University-Computer and Information Sciences*, 33(3):243–257.

Cao, Q., Yang, G., Wang, F., Chen, L., Xu, B., Zhao, C., Duan, D., Jiang, P., Xu, Z., and Yang, H. (2022). Discrimination of tea plant variety using in-situ multispectral imaging system and multi-feature analysis. *Computers and Electronics in Agriculture*, 202:107360.

Chen, X. and He, K. (2021). Exploring simple siamese representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 15750–15758.

Couasnet, G., El Abidine, M. Z., Laurens, F., Dutagaci, H., and Rousseau, D. (2021). Machine learning meets distinctness in variety testing. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1303–1311.

Dhanya, V., Subeesh, A., Kushwaha, N., Vishwakarma, D. K., Nagesh Kumar, T., Ritika, G., and Singh, A. (2022). Deep learning based computer vision approaches for smart agricultural applications. *Artificial Intelligence in Agriculture*, 6:211–229.

El Abidine, M. Z., Merdinoglu-Wiedemann, S., Rasti, P., Dutagaci, H., and Rousseau, D. (2020). Machine learning-based classification of powdery mildew severity on melon leaves. In *International Conference on Image and Signal Processing*, pages 74–81. Springer.

Garbouge, H., Rasti, P., and Rousseau, D. (2021a). Deep learning-based detection of seedling development from indoor to outdoor. In *International Conference on Systems, Signals and Image Processing*, pages 121–131. Springer.

Garbouge, H., Rasti, P., and Rousseau, D. (2021b). Enhancing the tracking of seedling growth using rgb-depth fusion and deep learning. *Sensors*, 21(24):8425.

Ghazal, S., Qureshi, W. S., Khan, U. S., Iqbal, J., Rashid, N., and Tiwana, M. I. (2021). Analysis of visual features and classifiers for fruit classification problem. *Computers and Electronics in Agriculture*, 187:106267.

Güldenring, R. and Nalpantidis, L. (2021). Self-supervised contrastive learning on agricultural images. *Computers and Electronics in Agriculture*, 191:106510.

Hu, C., Li, D., Song, Y.-Z., Xiang, T., and Hospedales, T. M. (2018). Sketch-a-classifier: Sketch-based photo classifier generation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 9136–9144.

Ireri, D., Belal, E., Okinda, C., Makange, N., and Ji, C. (2019). A computer vision system for defect discrimination and grading in tomatoes using machine learning and image processing. *Artificial Intelligence in Agriculture*, 2:28–37.

Ishikawa, T., Hayashi, A., Nagamatsu, S., Kyutoku, Y., Dan, I., Wada, T., Oku, K., Saeki, Y., Uto, T., Tanabata, T., et al. (2018). Classification of strawberry fruit shape by machine learning. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*, 42(2).

Jana, S. and Parekh, R. (2017). Shape-based fruit recognition and classification. In *International Conference on Computational Intelligence, Communications, and Business Analytics*, pages 184–196. Springer.

Jung, M., Roth, M., Aranzana, M. J., Auwerkerken, A., Bink, M., Denancé, C., Dujak, C., Durel, C.-E., i Forcada, C. F., Cantin, C. M., et al. (2020). The apple refpop—a reference population for genomics-assisted breeding in apple. *Horticulture research*, 7(1):1–16.

Kamilaris, A. and Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and electronics in agriculture*, 147:70–90.

Kheiralipour, K. and Pormah, A. (2017). Introducing new shape features for classification of cucumber fruit based on image processing technique and artificial neural networks. *Journal of food process engineering*, 40(6):e12558.

Koirala, A., Walsh, K. B., Wang, Z., and McCarthy, C. (2019). Deep learning–method overview and review of use for fruit detection and yield estimation. *Computers and electronics in agriculture*, 162:219–234.

Koklu, M., Cinar, I., and Taspinar, Y. S. (2021). Classification of rice varieties with deep learning methods. *Computers and electronics in agriculture*, 187:106285.

Kuhl, F. P. and Giardina, C. R. (1982). Elliptic fourier features of a closed contour. *Computer graphics and image processing*, 18(3):236–258.

Li, S., Luo, H., Hu, M., Zhang, M., Feng, J., Liu, Y., Dong, Q., and Liu, B. (2019). Optical non-destructive techniques for small berry fruits: A review. *Artificial Intelligence in Agriculture*, 2:85–98.

Li, Z., Guo, R., Li, M., Chen, Y., and Li, G. (2020). A review of computer vision technologies for plant phenotyping. *Computers and Electronics in Agriculture*, 176:105672.

Mahlein, A.-K. (2016). Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping. *Plant disease*, 100(2):241–251.

Meng, Y., Ma, Z., Ji, Z., Gao, R., and Su, Z. (2022). Fine hyperspectral classification of rice varieties based on attention module 3d-2dcnn. *Computers and Electronics in Agriculture*, 203:107474.

Pathan, M., Patel, N., Yagnik, H., and Shah, M. (2020). Artificial cognition for applications in smart agriculture: A comprehensive review. *Artificial Intelligence in Agriculture*, 4:81–95.

Schmidt, V., Goyal, K., Joshi, A., Feld, B., Conell, L., Laskaris, N., Blank, D., Wilson, J., Friedler, S., and Luccioni, S. (2021). CodeCarbon: Estimate and Track Carbon Emissions from Machine Learning Computing.

Simonyan, K. and Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

Szeliski, R. (2022). *Computer vision: algorithms and applications*. Springer Nature.

Zhang, X., Li, X., Liu, Y., and Feng, F. (2019). A survey on freehand sketch recognition and retrieval. *Image and Vision Computing*, 89:67–87.

Zine-El-Abidine, M., Dutagaci, H., Galopin, G., and Rousseau, D. (2021). Assigning apples to individual trees in dense orchards using 3d colour point clouds. *Biosystems Engineering*, 209:30–52.