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A low shot learning method for tea leaf's disease identification

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ABSTRACT

Tea leaf's diseases seriously affect the yield and quality of tea. This paper presents a low shot learning method for tea leaf's disease identification in order to prevent and control tea leaf's diseases timely. By extracting the color and texture features, disease spots on tea leaf's disease images are segmented by using support vector machine (SVM) method. With segmented disease spot images as input, new training samples are generated by the improved conditional deep convolutional generative adversarial networks (C-DCGAN) for data augmentation, which are used to train VGG16 deep learning model to identify the tea leaf's diseases. Experimental results show that, SVM can segment disease spot images on the condition of low shot learning while retaining the edge information well, improved C-DCGAN can generate augmented images with the same data distribution as real disease spot images, the VGG16 deep learning model trained with augmented disease spot images can identify tea leaf's diseases accurately, and the average identification accuracy of the proposed method reaches 90%, far exceeding classical low shot learning methods.

1. Introduction

China is an important tea producing and consuming country. In 2016, China's tea output was 2.41 million tons and 170.2 billion yuan, which occupied a considerable proportion in national economy (Qi and Zhang, 2016). Planting tea plants and producing high-quality tea are the main ways for tea farmers to obtain wealth, but there are about 130 kinds of tea leaf's diseases in China which will make tea plants grow poorly and reduce tea yields. Moreover, diseased leaves affect the quality of tea, which causes serious economic losses to tea farmers. Therefore, identifying the types of tea leaf's diseases accurately and taking corresponding preventive measures in time are of great significance for reducing the loss of tea yield, improving the quality of tea and increasing the income of tea farmers.

At present, the identification of tea leaf's diseases mainly relies on plant protection experts to conduct on-the-spot investigations and judge the categories of diseases based on experience. Artificial disease identification is expensive, and it is difficult for experts to reach the steep hills where teas are grown. Now machine learning and image processing methods have been widely used for plant disease identification. Chaudhary et al. classified multi-class groundnut diseases by combining an improved random forest machine learning algorithm, an attribute evaluator method and an instance filter method (Chaudhary et al., 2016). Tetila et al. compared the performance of different classifiers, including sequential minimal optimization (SMO), adaboost, decision trees, K-NN, random forest, and naive Bayes, for the identification of soybean foliar diseases (Tetila et al., 2017). Ehsan et al. proposed a fuzzy logic classification algorithm to improve classification efficiency for healthy and disease infected strawberry leaves (Ehsan and Tofik, 2017). Hossain et al. used support vector machine to identify two most widespread tea leaf diseases; brown blight disease and the algal leaf disease; in Bangladesh (Hossain et al., 2018). When these classical machine learning methods such as random forest, adaboost, decision trees and support vector machine are used to identify plant diseases, it is necessary to extract plant disease features which has a great influence on the identification accuracy. Since the tea leaves infected by different diseases have minor difference in color and texture, the identification accuracy of tea leaf's diseases is low by using classical machine learning methods.

The deep learning method developed in recent years does not require manual extraction of target features when performing target identification. If enough training samples are available, the identification accuracy of deep learning method is high. Zhang et al. proposed the improved GoogLeNet and Cifar10 models based on deep learning for the identification of maize leaf diseases. These two improved models were used to test 9 kinds of maize leaf images (Zhang et al., 2018). Ferentinos developed a deep learning method to perform plant disease detection and diagnosis. The training samples came from an open

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database of 87,848 leave images of healthy and diseased plants (Ferentinos, 2018). Lu et al. proposed a deep convolutional neural networks based method for rice disease identification. Its accuracy was higher than conventional machine learning model (Lu et al., 2017). Rangarajan et al. used a deep learning based architecture of AlexNet and VGG16 networks to classify tomato crop diseases. The training samples included 13,262 images (Rangarajan et al., 2018). Training the deep learning models above requires a large number of training samples. Due to insufficient funds, there are few tea leaf's disease test sites. It is difficult and expensive to collect enough tea leaf's disease data as training samples. The deep learning methods above are difficult to obtain high identification accuracy under the condition of insufficient available training samples of tea leaf's diseases.

This paper presents a low shot learning method for identification of tea leaf's diseases by using support vector machine and deep learning networks. Support vector machine is used for low shot segmentation of disease spots on tea leaf's disease images. Two deep learning networks, conditional deep convolutional generative adversarial networks (C-DCGAN) and VGG16 networks (Goodfellow et al., 2014; Simonyan and Zisserman, 2015), are combined to identify disease spot images. C-DCGAN can generate new disease spot images for augmentation of training samples which are used to train VGG16 classification networks to improve the identification accuracy. The schematic diagram of tea leaf's disease identification is shown in Fig. 1.

2. Materials and methods

2.1. Data sources

Part of the tea leaf's disease images used in this paper is taken in Tianjingshan National Forest Park, which is located in the south of Hefei, capital of Anhui Province, and surrounded by Chaohu Lake, one of the five major freshwater lakes in China. Its geographical coordinates are 31°14′37″ north latitude, 117°36′16″ east longitude, and 40 m above sea level. Image acquisition devices include a hand-held digital camera, which is Canon EOS 80D SLR camera, and an unmanned aerial vehicle, which is DJI phantom 4pro with 10-m flight altitude. Another part of the tea leaf's disease images come from Anhui Provincial Agricultural Committee's pest and disease agricultural graphic database. In this paper, three kinds of tea leaf's diseases, namely tea red scab, tea red leaf spot and tea leaf blight are selected.

2.2. Disease spot segmentation

Tea leaf's disease images are usually taken in the field with complex background which seriously interferes with the identification accuracy. In this paper, disease spots are segmented from tea leaf's disease images to remove complex background.

Images can be segmented by using unsupervised or supervised methods. Mortensen et al. proposed a method for segmenting lettuce in colored 3D point clouds. By clustering points into leaves, a lettuce of interest is discriminated with adjacent lettuce and non-lettuce (Mortensen et al., 2018). Reza et al. combined K-means clustering with a graph-cut (KCG) algorithm to segment the rice grain areas using low altitude RGB UAV images in order to estimate rice yield (Reza et al., 2018). Guijarro et al. proposed an automatic segmentation method for identification of three types of textures: green plants, soil and sky in agricultural images, where threshold approach is used for segmenting soil and sky (Guijarro et al., 2011). Because of the complex background in tea leaf's disease images; it is difficult to obtain good disease spot segmentation effect by unsupervised clustering method or threshold segmentation method.

Support vector machine (SVM) is suitable for high-dimensional, high-noise, few-shot learning. This paper uses SVM learning method to segment disease spots in tea leaf's disease images. Training and test samples of SVM are the feature vectors of healthy leaves and disease spots. The 4-dimensional color features are R, G, B three-channel pixel values and red-red index (2R-G-B) value. The 6-dimensional texture features are gray level co-occurrence matrix statistics including the means and standard deviations of energy, correlation and homogeneity. Fig. 2 shows partial segmentation results of disease spots.

2.3. Tea leaf's disease identification

Deep learning method is a popular target identification method at present, but it has over-fit problem in the case of small training set size. In recent years, deep convolutional generative adversarial networks (DCGAN) have been used for data augmentation (Radford et al., 2015; Curto et al., 2017). Conditional deep convolutional generative adversarial networks (C-DCGAN) can generate samples of specified types by adding conditional labels (Han and Yin, 2017; Ben-Cohen et al., 2019). This paper uses an improved C-DCGAN to generate different types of disease spot images to augment training samples. The augmented training samples are used to train VGG16 network to solve the over-fit problem and realize the accurate identification of tea leaf's diseases.

2.3.1. DCGAN

Generative adversarial networks (GAN) consist of generative networks G and discriminative networks D (Goodfellow et al., 2014). Generative networks are used to maximize the simulation of the original target data distribution and generate target samples. Discriminative networks are used to discriminate whether the generated samples are real samples or not. The objective function $V(D;\ G)$ of GAN is as follows:

$$\min_{G}\max_{D} V(D,\ G) = E_{m\ p_{data}(m)}[logD(m)] + E_{n\ p_n(n)}[\log(1 - D(G(n)))] \tag{1}$$

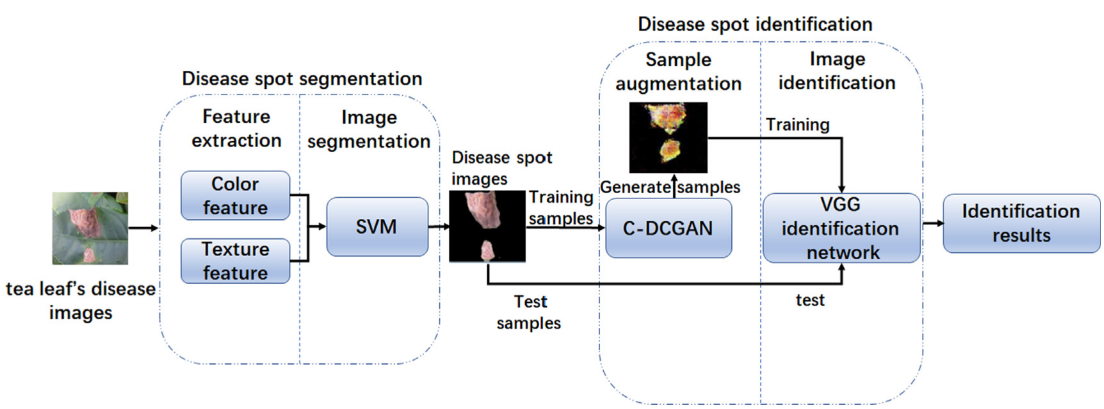

Fig. 1. Schematic diagram of tea leaf's disease identification.

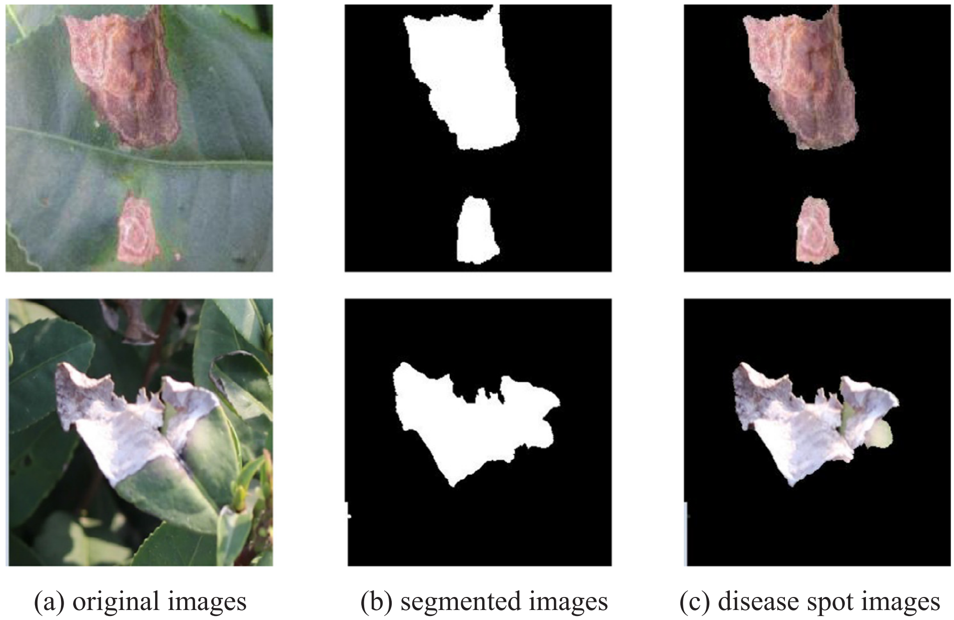

Fig. 2. Partial segmentation results of disease spots.

where m is a real sample, $D(m)$ represents the probability of discriminating m as a real sample by discriminative networks D, $G(n)$ is a sample generated from noise n by the generative networks G, and $D(G(n))$ indicates the probability of discriminating $G(n)$ as a real sample by discriminative networks D.

Radford et al. proposed DCGAN by introducing convolution neural networks (CNN) into GAN. DCGAN removes fully connected hidden layers for deeper architectures and replaces pooling layers with strided or fractional-strided convolutions (Radford et al., 2015). Compared with original GAN, DCGAN model has a deeper architecture and better feature representation.

2.3.2. C-DCGAN

With an additional condition c and noise n as input, DCGAN can generate specified types of images. DCGAN with conditional label constraint is called C-DCGAN, which is used to generate multiple types of disease spot samples in this paper.

Wasserstein generative adversarial networks – gradient penalty (WGAN-GP) loss function enables stable training by penalizing the norm of gradient of the discriminator with respect to its input (Gulrajani et al., 2017). Taking advantages of WGAN-GP loss function, this paper adds gradient penalty (GP) into the discriminative networks of C-DCGAN to prevent gradient collapse or gradient disappearance and improve the stability of the network. The objective function of C-DCGAN is defined as:

$$\underset{G}{min}\underset{D}{max}\, V(D, G) = E_{m\ p_{data}(m)} D(m|c) - E_{n\ p_n(n)} D(G(n)|c) - \lambda_{gp} E_{\hat{s}}[(||\nabla_{\hat{s}} D(\hat{s})||_2 - 1)^2] \quad (2)$$

where m is a real sample, n represents random noise, c is a conditional label, $\hat{s}$ represents uniform sampling of a pair of real and generated disease spot image, andλ_{gp} is the weight parameter. The weight parameter λ_{gp} is set to 10 in (Gulrajani et al., 2017), which according to our own experiments, is also the optimal value in this paper. The schematic diagram of generating disease spot samples by C-DCGAN is shown in Fig. 3.

2.3.3. Identification of disease spots based on VGG16 networks

After the training samples are augmented by the C-DCGAN above, deep learning methods can be used to identify disease spots. Traditional neural network methods have low identification accuracy, while methods like SVM use handcrafted features and are time-consuming when building models. Deep learning methods yield good results in identification tasks and don't need to manually extract features. They are used in this paper considering it is difficult to extract the intrinsic features of different plant diseases by artificial methods.

Compared to other deep networks, VGG16 networks use smaller convolution kernels and fewer parameters, which speeds up the network training speed and has more nonlinear transformations than a single convolution layer (Simonyan and Zisserman, 2015). This paper uses VGG16 networks to identify diseases spots. Firstly; training sample images are reshaped to the size of $128 \times 128 \times 3$. Then the multi-layer stacked convolution pooling layer is used to encode the images into $4 \times 4 \times 512$ potential vectors. Finally, the type probabilities of disease spots are regressed through three fully connected layers and the last softmax layer.

3. Experimental results and analysis

3.1. Disease spot segmentation results

The results of disease spot segmentation are shown in Fig. 4, where the threshold method, K-means clustering method, graph-cut method and the proposed method are compared. In Fig. 4, the proposed method almost completely segments disease spots from the tea leaf's disease images, while the other methods either cannot segment disease spots or segment disease spots incompletely. Threshold method, graph-cut method and K-means clustering method leave the information of healthy leaf on segmented disease spots. Threshold method may also lose the information of segmented disease spots. So compared with unsupervised segmentation methods, supervised segmentation method for low shot learning, such as SVM, has better segmentation results on tea leaf's disease images with complex background.

3.2. Tea leaf's disease identification results

3.2.1. Identification results of the proposed method and traditional machine learning method

In this experiment, 40 images of each type of tea diseases are selected. All 120 images are segmented to obtain disease spot images. 20 samples from each type of disease spot images are randomly selected as

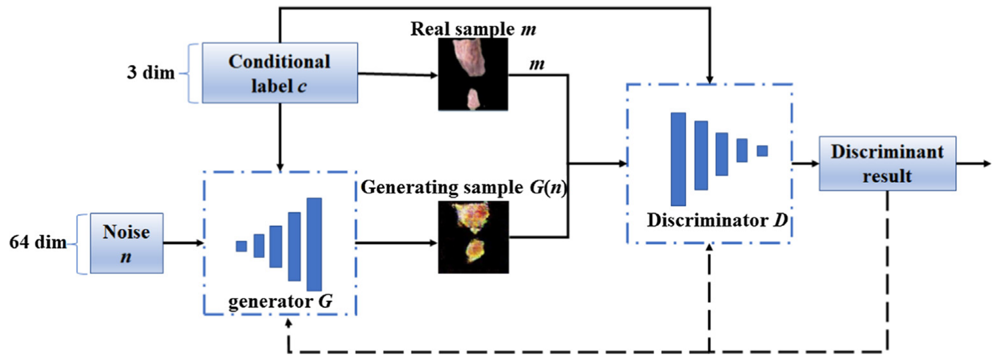

Fig. 3. Schematic diagram of generating disease spot samples by C-DCGAN.

training samples, and the remaining 20 samples from each type are used as test samples.

Color features and texture features of training samples are extracted, and classifiers of support vector machine, decision tree and random forest are trained respectively to identify test samples. Compared with traditional machine learning methods, training samples are input into C-DCGAN networks to generate 3 types of disease spot sample images, each of which has 4980 images. Then training samples are added to generated samples to obtain augmented training samples. VGG16 networks are trained with augmented training samples, and test samples are identified. The identification accuracies of different methods are shown in Table 1.

It can be seen from Table 1 that the proposed method is superior to traditional machine learning methods for tea leaf's disease identification. In the case of small dataset size, the identification accuracy can be improved by using deep learning model after sample augmentation.

Table 1
Identification accuracies of tea leaf's diseases by different methods.

Tea leaf's disease	SVM	Decision Tree	Random forest	C-DCGAN + VGG16
Tea red leaf spot	0.7	0.75	0.65	0.7
Tea leaf blight	0.6	0.6	0.8	1.0
Tea red scab	0.8	0.8	0.8	1.0

3.2.2. Identification accuracies using training samples augmented by different methods

In this experiment, VGG16 is trained with the following training samples: a. training samples augmented by C-DCGAN, b. training samples augmented by rotation and translation method, c. training samples without augmentation. The identification results are shown in Fig. 5. These results show that sample augmentation can improve the identification accuracy and avoid over-fit of deep learning networks for tea leaf's disease identification with insufficient training set size. The average identification accuracy using training samples augmented by C-DCGAN is about 28% higher than that of rotation and translation method. VGG16, as a deep learning method, is demanding of a large number of training samples. According to Fig. 5, VGG16 without data augmentation has a severe over-fit problem and the accuracy drops dramatically.

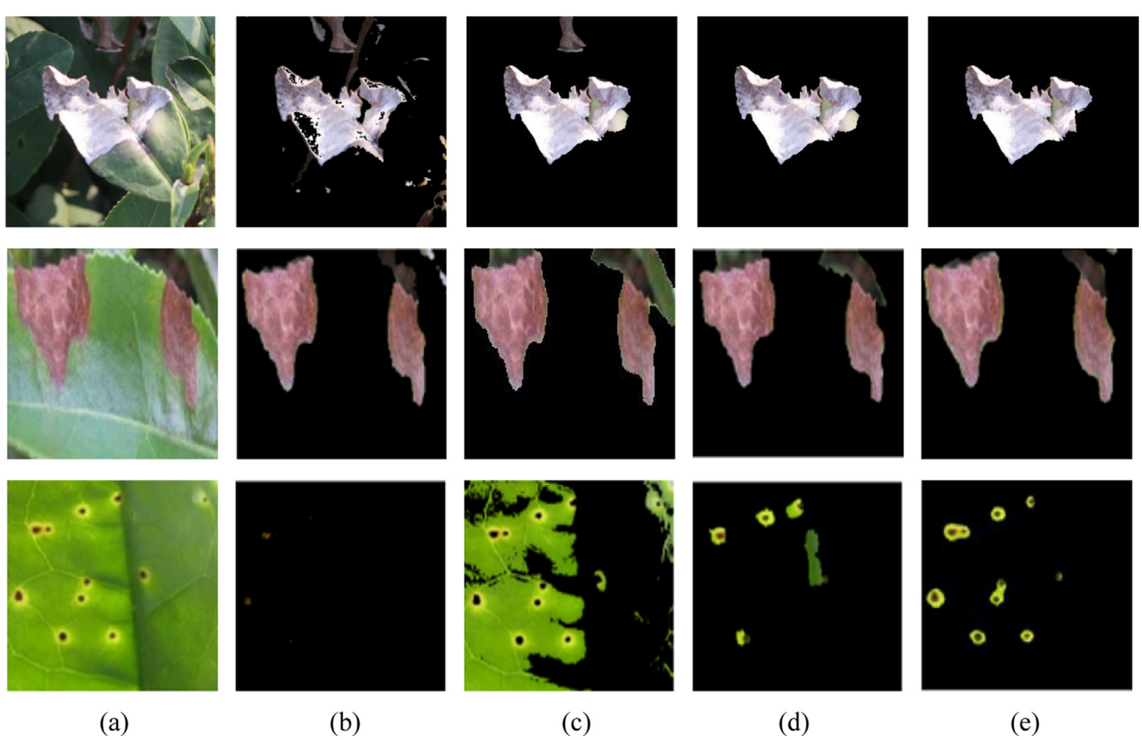

Fig. 4. Disease spot segmentation results. (a) the original images; (b) threshold segmentation results; (c) K-means clustering results; (d) Graph-cut results; (e) the proposed segmentation results.

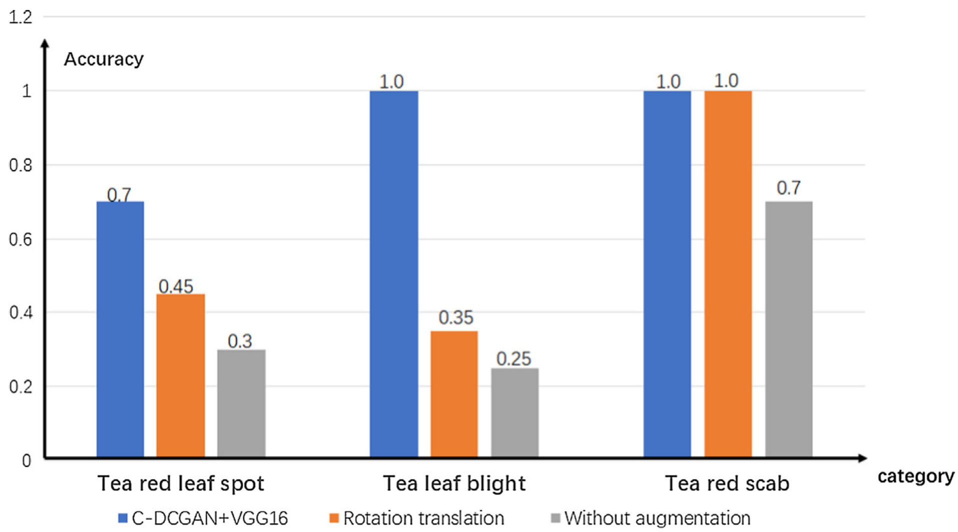

Fig. 5. Comparison of identification accuracies using training samples augmented by different methods.

3.2.3. Identification accuracies by using disease spot images or original tea leaf's disease images

Using segmented disease spot (DS) images and original tea leaf's disease (TLD) images as training samples, the average identification accuracies of different methods are given in Fig. 6. Because of the limitation of photographic conditions and field scenes, TLD images have complex backgrounds and strong noises. When C-DCGAN is used to generate training samples, these backgrounds and noises are amplified, which affects the identification accuracy of VGG16 networks. Fig. 6 shows that, for all methods, segmenting disease spots from tea leaf's disease images can effectively improve the accuracy of identification. The average identification accuracy by using DS images is about 21.5% higher than that by using TLD images.

4. Conclusions

Deep learning method is an effective method of identifying tea leaf's diseases, but the training of deep learning model needs a large number of training samples. Due to the limitation of practical conditions, it is difficult to collect enough samples of tea leaf's diseases. This paper proposes a low shot learning method for tea leaf's disease identification. Tea disease spots are segmented from tea leaf's disease images by SVM. The disease spot samples are augmented by C-DCGAN, and VGG16 deep learning networks are trained to realize disease spots identification. Experimental results show that the combination of traditional machine learning methods and deep learning methods can effectively identify tea leaf's diseases with complex background. The average identification accuracy of tea red scab, tea red leaf spot and tea leaf blight reaches 90%, which is more than 30% higher than that of SVM. The next step is to find a better data generating method and a low shot learning method with strong generalization performance, so as to improve the robustness and accuracy of tea leaf's disease identification with few training samples.

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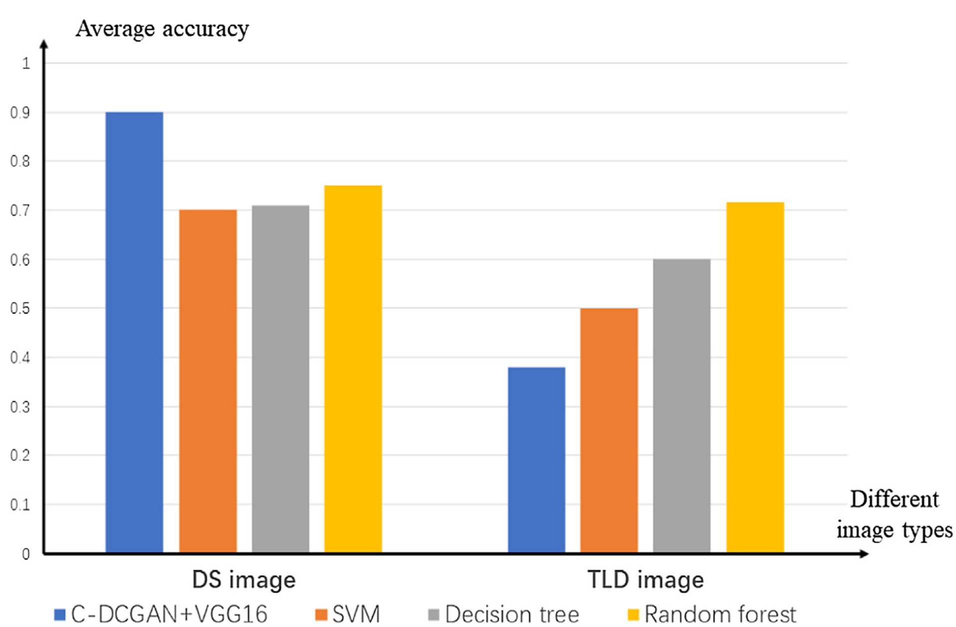

Fig. 6. Comparison of identification accuracies of different methods using DS images or TLS images.

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