Cotton Appearance Grade Classification Based on Machine Learning

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Abstract

In recent years, due to the rapid development of Chinese textile industry, the domestic demand for cotton increases sharply. Conversely, the cotton plantation area increasingly dwindled, resulting in the constant rise of cotton imports. China, as a great cotton importer, has classified manually the cotton grades for a long time, which not only results in a consumption of labor and financial resources, but also leads to some mistakes generated by the labor's subjective evaluation. This paper presents a method for automatic cotton classification for different appearance grades. Based on a comprehensive comparison, our method performs better in the classification of cotton appearance grades. PCANet feature recognition with basic impurity identification achieves the best performance.

1 Introduction

Cotton is one of the main crops and imported commodity in China, as well as a special imported commodity for inspection and quarantine. In recent years, the rapid development of the domestic cotton textile industry has led to an increasing demand for cotton, and the need in the domestic cotton market increased. However, due to the constant decline in the domestic cotton plantation area, China imports a large quantity of cotton every year. In 2010, cotton imports were 2.67 million tons, rose up to 3.3 million tons in 2011, until reaching 5.13 million tons in 2012 [1].

In the cotton inspection, its appearance grade is one of the most important factors reflecting the quality of cotton, also one of the most decisive factors of cotton price, playing an important role in the cotton import and export trade. The manual grading method by determining against physical standards or transactional samples have been used for so many years. There are certain drawbacks in Grade-level manual inspection, including huge manpower requirement, low inspection efficiency, and significant influence from inspection conditions such as light. What's more, human error can occur regularly because of long inspection time. How to eliminate these unfavorable factors has been the focus of research for the cotton testing industry.

Nowadays, Deep Revolution Networks became more and more popular in image classification and object detection. Deep learning is a method of machine learning. In recent years, the ability to accurately identify and predict deep learning has continued to increase [5]. What's more, deep learning continues to be used in a growing number of practical problems. As the convolutional network won the ImageNet contest, the error rate of top5 reduced from 26.1% to 15.3%. Since then, deep learning has won such competitions in succession until the error rate reduced to 3.6% in 2015. With the increasing size and accuracy of deep networks, the tasks can be solved becomes more and more complex. This increasing trend of complexity has pushed it to logical conclusions, such as the introduction of Neural Turing Machines [22], which can learn to read memory cells and write arbitrary content to memory cells. Such a neural network can learn simple programs from a sample of expected behaviors. For example, learning from a messy and well-ordered sample to sort the series. In principle, this approach can be applied to almost any task in the future.

In our experiments, the images of cotton were collected, and their corresponding features were extracted from the images using a deep convolutional neural network to characterize the cotton appearance. Finally, a highly robust classifier was trained using machine learning techniques to realize an automatic classification of cotton grades.

2 Related Works

Cotton in different countries has its own appearance grade assessment criteria. In order to achieve the instrumentation of cotton inspection, the United States developed the HVI (High Volume Instrument) machine in 1970s as shown in Figure 1. This test was originally used by the US Department of Agriculture (USDA) to test the properties of cotton fibers. It was later developed into a widely used testing equipment in the cotton production, trade and textile industries. HVI system is now the main basis for cotton grading in the United States and became an international advanced cotton testing instrument. It can be used to detect impurities and cotton fiber maturity. Large-capacity testing instruments can further detect sugar content, fineness, single fiber strength, color and classify cotton. In the HVI inspection project, "color" and "trash" attributes are related to the appearance grade of cotton. The "color" attribute is determined by reflectance (Rd) and yellowness (+b). The reflectance and yellowness are obtained by photodetectors and color filters. The "trash" attribute measures the amount of impurities in cotton.

The USDA has worked on the instrumentation of cotton color inspection since the 1930s, but the colorimeter technology was only integrated into HVI in the 1970s. However, the results from HVI assessment differed from the results from manual classification, with only 70% of the classification results consistent. A large research community around the world focus on this research field to achieve a better matching between them. Lieberman M. et al. [20] apply the clustering method of neural network to the classification of cotton impurities; Xu B. et al. [3] use color and geometric features as descriptors of impurities. For this purpose, the authors compare and analyze the sum of squares, fuzzy logic and neural network. Accuracy and function of three clustering methods are the main criteria for cotton impurity classification. from the perspective of spectroscopy and image analysis, Duckett K. et a. [6] proposed in 1999 the use of the a* of the CIE La*b* color space and the variance of the yellowness as HVI test items to improve the instrument test results and manual test results. In 2002, Xu B. et al. [2] constructed a fuzzy inference system (FIS) based on fuzzy logic theory for the boundary blur and coverage problems in the adjacent levels of color cotton grading, providing very satisfactory results. Matusiak M. [4] gives a comparison of the HVI results with the manual classification results for on US-imported cotton. In addition, it is demonstrated that there is a strong correlation between the reflectance

Rd in HVI and CIE L* measured by spectrophotometer. The above research results have motivated the design for our network.

Principal Component Analysis Network (PCANet) is a simple PCA filter-based convolutional network structure proposed by Chan et al. [1], which consists of an input layer, two convolutional layers and an output layer. PCANet is a very simple deep learning network that efficiently extracts useful

Figure 1: The HVI (High Volume Instrument) machine developed by the United States in 1970s

information from facial, digital and texture image classifications.

VGGNet[12] is the deep convolutional neural network, developed by the University of Oxford's Visual Geometry Group and researchers at Google DeepMind. It achieved second place in ILSVRC 2014 by reducing the Top-5 error rate to 7.3%. Its main contribution is to demonstrate that the depth of the network is a key part of the good performance of the algorithm. At present, the network structures that are used in much more fields include ResNet (152-1000 layers), GoogleNet (22 layers), and VGGNet (19 layers). Most of the current models are improved based on these several model improvements by using new optimization algorithms, multiple models fusion and so on. So far, VGG Net is still often used to extract image features.

3 Data Acquisition and Image Processing

3.1 Data Acquisition

The grades for US upland cotton are divided into 5 categories: including White, Light spotted, Spotted, Tinged, Yellow stained. This paper uses US upland cotton as the main research object. Based on the US upland cotton assessment criteria, different grades of cotton samples were collected. They are divided into 7 levels (the quality is decremented in order), which are: Good Middling, Strict Middling, Middling, Strict Low Middling, Low Middling, Strict Good Ordinary, Good Ordinary.

This paper uses an industrial camera for the collection of US cotton data with a high import volume. The collection range is: the non-standard box samples of Strict Middling (SM) and Middling (M) which are common in import and export trade. In order to ensure a consistent environment for each acquisition, this paper designed a light box for cotton sample collection, using a standard D65 light source consistent with the ambient light of the cotton testing laboratory. The D65 source is the most commonly used artificial daylight in standard light sources with a color temperature of 6500K. Because the color characteristics of cotton have a great influence on the appearance of cotton, the quality of the captured image seriously affects the later estimation. And the camera is at the same height as the light source, and the camera line of sight is perpendicular to the cotton disposition, thereby reducing the shadowing effect in the image, as shown in Figure 2.

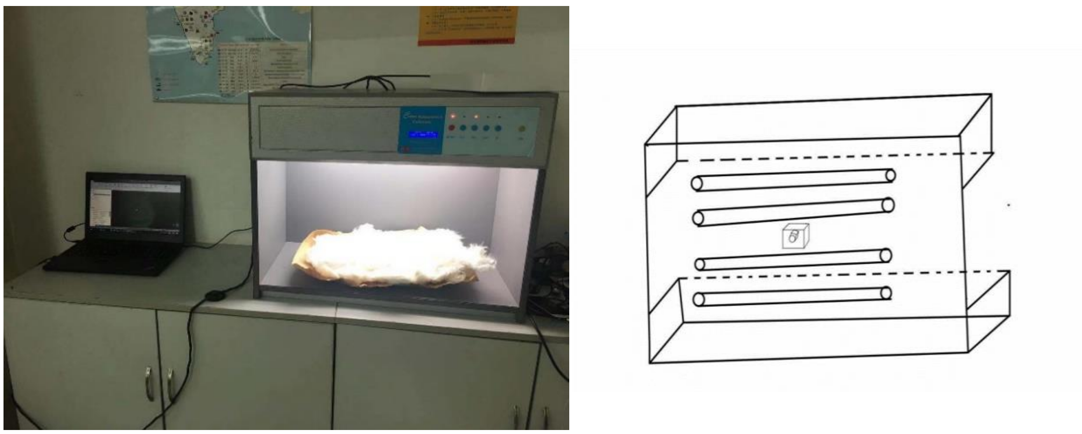


Figure 2: The light box for image data collection. On the left picture, the light box is being used. The inner structure of the light box is shown on the right, including four D65 light tubes and an industrial camera directly connected to the computer.

And the acquired image samples showed on Figure 3.

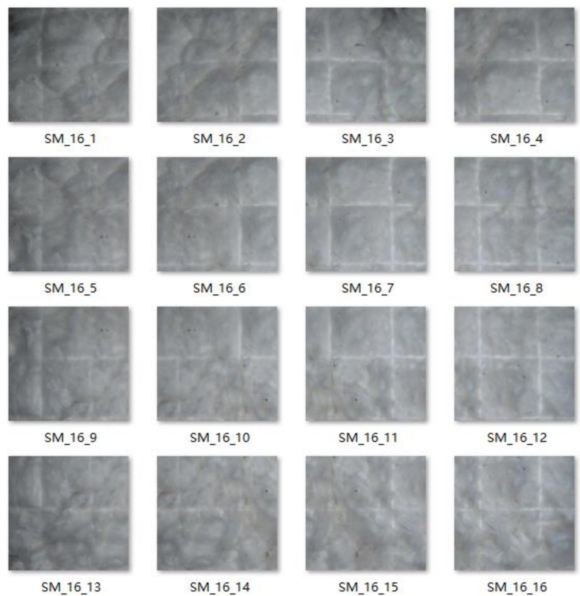
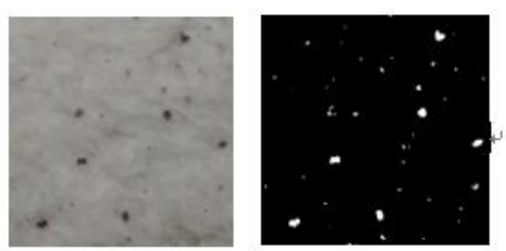


Figure 3: The image collected and cropped using the designed light box, the X in SM_16_X is the number of the images which is cropped from the picture named SM_16.

3.2 Image Pre-processing

Since the influence of impurities on the cotton appearance quality inspection is large, this paper preliminarily identifies the cotton image. In the impurity identification process, the image is normalized, and the edge is searched from the gray level change based on the normalized image, thereby improving the robustness of our method. After this step, the Sobel operator is used to perform edge detection on the normalized image to obtain its corresponding binary image, which is then Threshold to obtain another binary image. The resulting two images are combined by an AND logical operator, and finally



(a) (b)

Figure 4: Impurity recognition image, (a) is the original cotton image, (b) is the impurity recognition result.Section headings

the impurities of only one pixel are removed by eliminating the noise points. Figure 4 shows the results of impurity identification.
And Figure 5 exhibits the results of the seven levels of impurities.

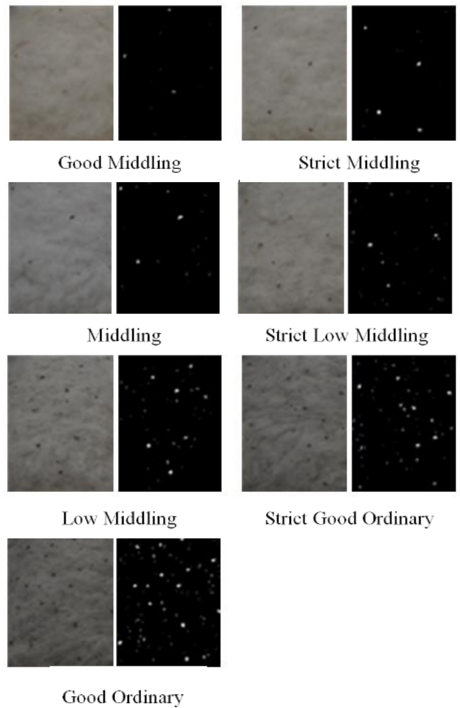


Figure 5: Impurity recognition resulting graph for the seven US upland cotton levels. Between the two pictures of each grade, the left side of each graph is a sample, and the right side is the impurity identification result.

4 Methods

4.1 Feature Extraction

In this section, we investigated the performances of different feature extraction methods on cotton appearance. We extracted the 500×500pixel non-standard box cotton images using different methods, and extracted the result as the input of the classifier, and finally compared the classification results. Due to many factors affecting the cotton appearance, this paper selects three-typical computational features including one hand-crafted feature and two deep network features, Gabor wavelets, PCANet, VGGNet, to extract the comprehensive cotton features.

4.1.1 Principal Components Analysis Network

PCANet is a common data analysis method, transforming the original data through linear changes into a set of linearly independent representations of each dimension. The main idea is to extract the main feature components from the input data, and to discard the redundant information and the least relevant data for dimensionality reduction and compression. PCANet achieves good results on many object recognition datasets.

Figure 6 shows a schematic diagram of the PCANet architecture. The input image goes through two convolutional layers, where the number of filters in the first layer is L1 while in the second layer is L2. After two layers of convolution, the corresponding L_1L_2 output convolution images are obtained for each input image. The image outputs from the second convolutional network are binarized and then combined with different weights into an image whose range value belongs to (0; 2^{L_2}-1). Each of these images is partitioned into blocks, in which a histogram is performed. All these histograms are used as output features of PCANet.

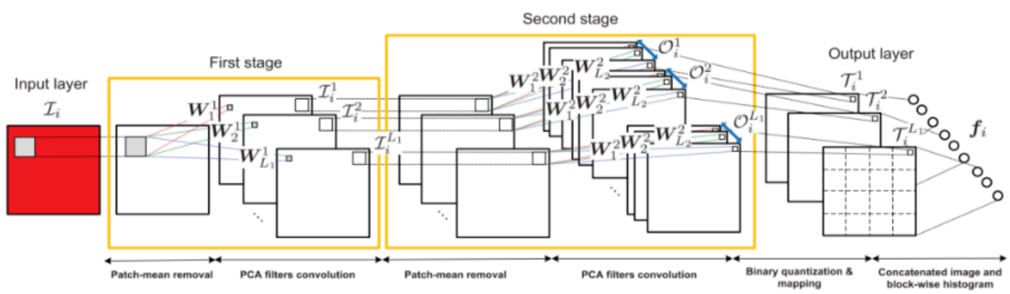


Figure 6: A detailed block diagram of the (two stages) PCANet [1]

In this paper, the texture image size is 256×256. When extracting PCANet features, the filter is set to 8×8, the number of filters in each layer is 8, and the size of the histogram partition is 24×24. Knowing that the high-dimensional feature calculation requires high computer memory, we use the PCA dimension reduction toolbox (drtoolbox) to perform PCA dimensionality reduction on the extracted features, and select the most prevalent 48-dimensional features as our PCANet feature.

4.1.2 VGGNet

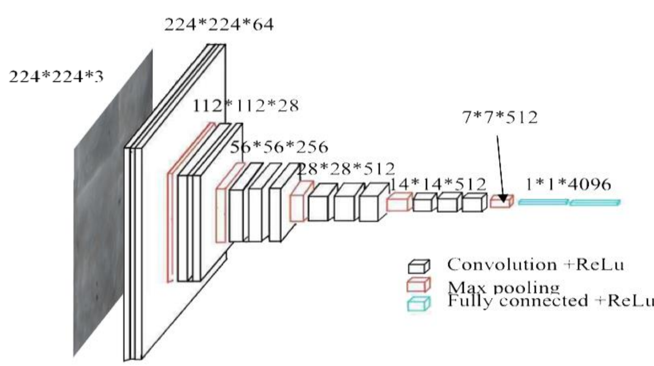


Figure 7: A detailed block diagram of the VGGNet [12]

VGGNet [12] uses 3×3 convolution kernel size and 2×2 pooling size. Each convolution layer contains 2~4 convolution operations. Using a convolutional layer of multiple smaller convolution kernels than the single convolutional layer with a larger convolution kernel reduces parameters. On the one hand, it can reduce the parameters. And on the other hand, it can make more unqualified mappings. The computational cost is reduced, and in the training, the A-ConvNet with a shallow layer is trained first, and the weight of the A-ConvNet is used to initialize the later complex model to speed up the training convergence. Figure 7 shows the VGGNet architecture

During the use of VGGNet, we resize the 256*256 cotton image into 224*224 as inputs. VGGNet is composed of a series of convolution layers, with five interposed max pooling layers, followed by three fully connected layer. It has a convolution layer stride of 1 pixel, and the padding of the 3*3 convolution layer is set to 1 pixel. The max-pooling window is 2*2 and the step size is 2. The first two fully connected layers named 'fc7' and 'fc8' have 4096 channels, and the third one has 1000 channels, followed by a Softmax operation for output classification. Finally, the feature of the first 4096-dimensional layer – 'fc7' is selected according to the feature dimension and the performance of the computer.

4.1.3 Gabor Filter

The Gabor transform is also called window Fourier transform or short-time Fourier transform. The Gabor transform breaks through the Fourier transform of the problem that the Fourier transform cannot obtain the order relationship between different frequencies, and realizes the extraction in different scales and directions in the frequency domain. The Gabor transform is very similar to the visual stimulus response of simple cells in the human visual systems, and has good characteristics in extracting the local spatial and frequency domain information from the target.

The Gabor feature, consistent with human visual perception, is used to describe image texture information. Its Gabor wavelet transform can be defined by the following convolutional form:

$$G_{mn}(x,y) = \sum\sum I(x-s,y-t)\,\psi_{mn}^{*}(s,t) \tag{1}$$

where s and t are used to indicate the filter size, and x and y are used to indicate the pixel position in the image. Continuous wavelet function dependent on parameter (a, b) generated by wavelet generating function $\psi(x)$. The Gabor wavelet is obtained by generating a function defined as:

$$\mathrm{g_{mn}(x,y) = a^{-m}g(x',y')},\ \ \mathrm{a} > 1, m, n = integer \tag{2}$$

where $x' = a^{-m}(xcos\theta + ysin\theta)$, $y' = a^{-m}(-xsin\theta + ycos\theta)$, $\theta = \frac{\mathrm{n\pi}}{\mathrm{K}}$. What's more, m and n represent the scale and direction of the filter, respectively, m = 0, 1, ⋯, S-1; n = 0, 1, ⋯, K-1. S represents the total number of scales, and K represents the total number of directions. After the filter is constructed, the image is convoluted using a filter.

$$\mathrm{W}_{mn}(x,y) = \int I(x_1,y_1)\,g_{mn}^{*}(x-x_1,y-y_1)dx_1dy_1 \tag{3}$$

$\mathrm{W}_{mn}(x,y)$ represents the image after convolution, whose feature dimension is relatively large, thereby relatively complex to compute. In order to reduce the dimension and to compress the convolved image, the image information is represented by its mean and variance. The means is

$$\mu_{mn} = \iint |W_{mn}(x,y)|dxdy\,, \tag{4}$$

and the variance is

$$\sigma_{mn} = \sqrt{\iint (|W_{mn}(x,y)| - \mu_{mn})^2\,dxdy} \tag{5}$$

Therefore, the resulting feature vector is $\mathrm{f} = [\mu_{00}\,\sigma_{00}\,\cdots\,\mu_{S-1K-1}\,\sigma_{S-1K-1}\,]$. The Gabor feature used in this experiment was extracted using a filter with 4 scales and 6 directions, giving the feature dimension of 48 dimensions.

In addition, the Gabor wavelet is sensitive to the edges of images and extract texture information in different direction, making it an efficient method for direction selection and scale selection. Besides, The Gabor filter is insensitive to illumination changes, providing good adaptability to illumination changes, tolerate a certain degree of image rotation and deformation.

4.2 Image Classification—Support Vector Machine

Support Vector Machine (SVM) is another optimal design algorithm proposed by Vapnik et al. [21] based on the statistical learning theory for linear classifiers, which makes the learner globally method. The idea of the SVM method is mainly to directly analyze linearly separable cases; for the linearly non-separable case, a low-dimensional space sample is transformed into a high-dimensional feature space to make it linearly separable. This algorithm uses the expansion theorem of the kernel function, and determines different SVMs depending on the kernel function type. Through this method, the nonlinear characteristics of samples are successfully analyzed linearly in the high-dimensional feature space.

In the process of using SVM method for classification, this paper separately compares multiple feature extraction results with corresponding labels and uses the same method to shuffle the order as input. 80% of the datasets were used as training set and the remaining 20% were used as test seta, test the resulting classifier.

5 Datasets

In this paper, different methods are applied to standard data sets and non-standard data sets. Among them, the standard data set is derived by Zhang Ting[13], including 7 levels of US upland white cotton totaling 784 sheets; the non-standard data set is derived from the SM level and M level collected in the cotton inspection laboratory, and the images of different sizes are 150 sheets. In the experiment, the non-standard images were pre-cut to the same size of 500*500 pixels, a total of 2634 sheets.

6 Experiments

Color, impurities and rolling mills are the three major factors that a trained worker considers when judging the grade of cotton. This paper tests the performance of different feature extraction methods in standard dataset samples. The existing 700 standard 500*500pixel dataset images are cropped into 3024 images of 256*256 pixel with a simple code and correspond to the matched labels. Firstly, the impurity recognition pre-processing on 3024 image samples is carried out to obtain the corresponding binary image before extracting their features using PCANet. These features and level labels are shuffled in the same way. 2420 images out of the 3024 dataset images are used as SVM. The training set for the classifier, the remaining 604 images, are used as test set.

VGGNet extracts 3024 clipped images, and selects the fc7 layer features and level labels in the same way mainly according to the data size, and then classifies 2420 images as SVM training set, the remaining 604 images as test set.

Gabor Filter extracts 3024 clipped images, whose features and level labels are shuffled in the same way, and puts them into the SVM classifier in the same proportion as above for training and testing.

At the same time, we used the same method to compare the performances of different feature extraction methods on the cotton appearance accuracy for non-standard dataset samples using the same classifier.

Finally, we compare the accuracy of these classification experiments as shown in Table 1 and Table2. Table 1 shows the accuracy of different feature extraction methods which is used for the classification of standard boxes cottons. And Tables 2 shows it for non-standard boxes cottons.

In terms of cotton appearance grade classification, the classification results of ordinary PCANet and VGGNet without impurity identification are very similar. We also compared the classification results of PCANet with impurity identification with other methods. PCANet, which has previously identified impurities, has a better performance in the standard dataset than the most advanced VGGNet, and its

Datasets	Methods	Accuracy
Standard Box	PCANet + SVM	90.7%
Standard Box	PCANet + SVM (Impurity identification)	98.9%
Standard Box	VGGNet + SVM	89.9%
Standard Box	Gabor + SVM	85%

Table 1: Accuracy of different feature extraction methods in cotton appearance grade classification

Datasets	Methods	Accuracy
Non-Standard Box	PCANet + SVM	71.8%
Non-Standard Box	PCANet + SVM (Impurity identification)	76.8%
Non-Standard Box	VGGNet + SVM	71%
Non-Standard Box	Gabor + SVM	68.5%

Table 2: Accuracy of different feature extraction methods in cotton appearance grade classification

accuracy is 9% higher than VGGNet. For the Non-Standard dataset, the accuracy of PCANet + SVM is exactly 5.8% higher than VGGNet + SVM. Then, we could conclude on the importance of the impurity identification pre-process.

7 Conclusion

This paper introduced cotton grade classification algorithms based on Deep Revolution Networks from three aspects: data acquisition and image preprocessing, feature extraction, and classifier design. In this paper, the VGG network is used to preprocess the dataset, extract relevant computational features, and then the extracted computational features are used to train a classifier using principal component analysis to achieve automatic classification of cotton grades.

Nowadays, as the degree of manufacturing and industrial automation increases, more and more manual work is progressively automated. For enterprises, this trend not will not only save resources and improve efficiency, but also avoid some regular human measurement uncertainty. Cotton grade classification is now basically using the manual rating method. Based on digital image processing algorithms, machine learning technology and deep learning methods, this paper searches for a feature extraction method for automatic cotton grade classification with high accuracy. Next, we will continue to research for methods with higher accuracy based on the method of this paper.

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