IEEE INSTRUMENTATION & MEASUREMENT SOCIETY

Received 15 May 2022; revised 23 June 2022; accepted 25 June 2022. Date of publication 12 July 2022; date of current version 25 July 2022.
The review of this paper was arranged by Associate Editor P. Wang.

Digital Object Identifier 10.1109/OJIM.2022.3190024

Deep Neural Network-Based Sorghum Adulteration Detection in Baijiu Brewing

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This work was supported by the Tsinghua University–Luzhou Laojiao Joint Research Center for Intelligent Detection.

ABSTRACT In Baijiu brewing process, suppliers may adulterate glutinous sorghum with commercially inferior japonica sorghum, which can affect the yield and quality of the final Baijiu production. Currently, sorghum adulteration detection in Baijiu brewing process in China is carried out manually by sampling and observation, which strongly depends on the experiences of workers. In this paper, we proposed a method that uses sorghum images as input and combines image processing and deep neural networks to identify grain varieties and calculate the adulteration ratio. Two derivative networks of CNN, i.e., ResNet and SqueezeNet are used to implement the deep neural networks for sorghum grain identification and adulteration ratio calculation. The classification accuracy of the ResNet and SqueezeNet based models reached 93.34% and 87.98% on test set, respectively. The root mean squared error (RSME) for adulteration ratio estimation is 4.95% and 7.73%, respectively. The mean absolute error (MAE) is 4.20% and 6.29% accordingly. The proposed pipeline is capable of realizing rapid and non-destructive adulteration detection of raw materials in industrial production, thus conducing to the industrial digital transformation and efficiency improvement.

INDEX TERMS Adulteration detection, brewing process, deep learning, image processing, machine vision.

I. INTRODUCTION

CHINA has a very long history of Baijiu production and consumption. Currently, Chinese Baijiu manufacturing industry is still a labor-intensive industry with a low degree of mechanization and automation. With the development of economy and the new requirements for energy conservation and emission reduction, more and more attention has been paid to the digitalization and modernization of Baijiu production process.

Solid state fermentation is the common production way of typical Chinese Baijiu brewing process, which uses in different production stages a variety of granular materials including grain, Daqu starter, rice husk, bran, etc. Among these materials, grain is the source where Baijiu comes from by fermentation. Most of famous Baijiu in China use sorghum as the main raw material grain due to the fact that the nutritional composition and physical properties of sorghum result in high alcohol yield and mellow brewing, which is far superior to other grain crops such as corns, wheat, potatoes and beans [1], [2]. In market, there are basically two typical sorghums available, which are glutinous sorghum and japonica sorghum. It is found that amylose, amylopectin, protein, tannin, fat and other components of sorghum from different origins and varieties are also different. Meanwhile, studies have shown that the aforementioned different properties of sorghum will ultimately affect the quality and yield of Baijiu. In comparison to using japonica sorghum, ethanol yield and fermentation efficiency of using glutinous sorghum can be improved significantly [3], [4]. On the other hand, japonica sorghum is usually much more cheaper than glutinous sorghum. For this reason, there exists sometimes that japonica sorghum, due to its relatively low cost, is mixed into glutinous sorghum by certain small suppliers, which destroys the consistency of brewed product quality and reduces production efficiency. Although great effects have been made to reduce this risk by selecting high-quality suppliers, there still exists the possibility that glutinous sorghum mixed with japonica sorghum is supplied due to the huge demand for this raw materials. Therefore, it is necessary and important to monitor the source and variety of sorghum raw materials in the process of solid-state Baijiu brewing.

Currently, most of Baijiu manufacturers still use the traditional method by manual sampling and observation and screening to conduct sorghum raw material inspections, which depends heavily on the workers' experiences. From the perspective of digitalization and modernization of Baijiu production process, it is necessary and there is still a large room to develop the related sorghum adulteration detection techniques to enhance the accuracy and improve the production efficiency.

Literature reviews show that certain number of related studies have been done on in laboratory to detect or identify different varieties of granular raw materials in food manufacturing related areas by using different measurement and instrumentation techniques including biochemical methods, near infrared spectroscopy, Raman spectroscopy and hyperspectral imaging [5]–[9]. Eksi-Kocak *et al.* combined Principal Component Analysis (PCA) and Partial Least Squares Regression (PLSR) to quantify adulteration in pistachio granules and green peas by Raman spectroscopic imaging [5]. Verdú *et al.* studied the ability of short-wave near-infrared hyper spectroscopy by capturing hyperspectral images of flour and processed breadcrumbs to detect the incorporation of wheat flour and bread into inexpensive grains such as sorghum, oats and corn [6]. Anami *et al.* extracted color and texture features from bulk paddy samples, employed PCA for feature selection, and obtained adulteration level classification accuracy of 93.31% using Multilayer Back Propagation Neural Network (BPNN) model [7]. Based on morphology analysis and near infrared spectral data, Vermeulen *et al.* used Partial Least Squares Discriminant Analysis (PLSDA) and developed a method to identify common wheat adulterated with durum wheat, which achieved the qualitative adulteration detection accuracy up to 99% [8]. Bai *et al.* used the watershed algorithm to extract hyperspectral data from sorghum, removed abnormal samples through PCA and clustering analysis, identified the cultivar of the samples, labelled varieties using different colors to obtain sorghum distribution maps and adulteration rates, which achieved a fast and non-destructive detection of adulteration in sorghum with an accuracy near 90% [9]. Thus far, most of these studies are conducted in laboratory, which is quite different from the practical production scene and difficult for practical industrial field applications.

As a matter of fact, the traditional manual observation and identification for sorghum adulteration detection in China Baijiu brewing industrials is very common and can provide successful application results from well experienced technical workers. This implies that there is a great potential to identify both japonica and glutinous sorghum and further calculate adulteration ratio by using vision sensors such as CCD or CMOS cameras and computer vision based image processing methods. In our previous work, we have proposed machine vision based measurement system together with traditional machine learning method such as support vector machine (SVM) to implement sorghum adulteration detection by using sorghum particles shape, size distribution, and different color histograms including RGB, HSV and CIELAB as features [10]. The preliminary experimental results show that our proposed machine vision based method and SVM model with radial basis function (RBF) kernel achieved a validation accuracy of 84.71% on a small scale dataset for the classification of glutinous sorghum and japonica sorghum, which has a large room to improve. From this perspective, by considering the tremendous success of deep learning in recent years, this study proposes a method based on machine vision together with deep neural networks for identification of sorghum varieties and adulteration detection.

The organization of this article is as follows. In Section II, the scheme of our proposed machine vision together with deep neural networks for identification of sorghum varieties and adulteration detection is introduced in detail. Based on this principle, two deep neural networks of CNN, i.e. ResNet and SqueezeNet, are implemented for this purpose. In Section III, the experimental results and discussions are presented. Finally, the conclusions are drawn in Section IV.

II. DEEP NEURAL NETWORK BASED METHODS

Fig. 1 depicts the scheme of our proposed deep neural network based method for sorghum adulteration detection, which is composed of three main procedures including data preparation, image processing and deep neural network based classification. Fig. 2 depicts the instrumentation system for identification of sorghum varieties and adulteration detection.

A. DATA PREPARATION

The regular practice for training classifiers with deep neural networks needs to collect large amounts of labeled data for supervised learning. Regardless of the network structures and different types of models, the quality and scale of the dataset has a significant impact on the classification performance. Therefore, the acquisition of original images plays a fundamental part in overall project.

As shown in Fig. 2, we used Sony IMX430 CMOS sensor with screen resolution of 1624×1240 to capture the images of sorghum particles. Sorghum granules were deposited in open containers with white bottom which was placed on a vibrating base to simulate the situation of industrial production conveyor belt transportation process. For the same batch of particles, we shot video for around one minute, then extracted the images from the recorded video sequence in the rate of one image every 10 frames. This way can ensure adequate collection of sorghum images from the same batch and avoid model overfitting due to duplicated images.

The vibrating base can disperse the granules as much as possible, which is convenient for subsequent image processing. Considering the fact that sorghum granules have

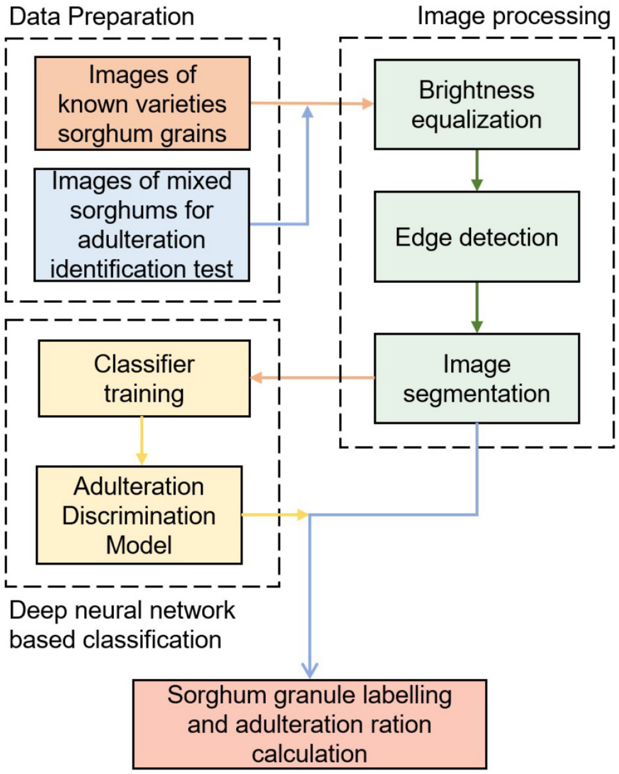


FIGURE 1. Flowchart of the proposed methodology.

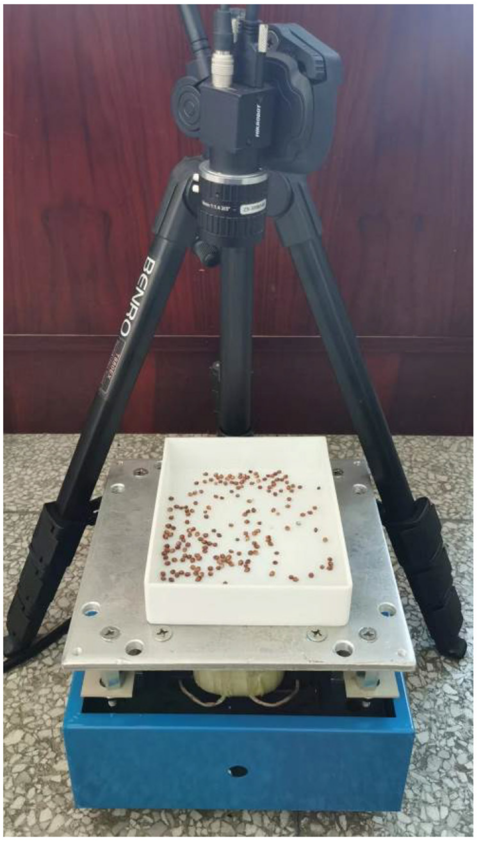


FIGURE 2. Images acquisition setup.

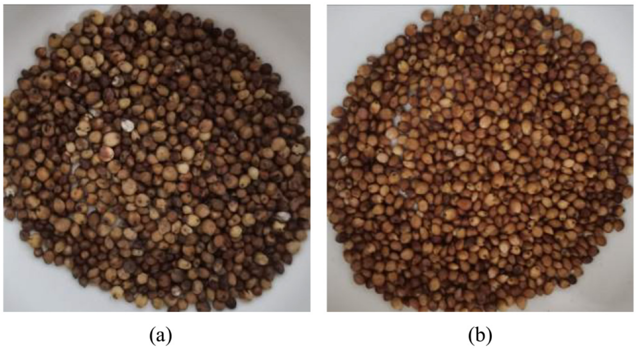


FIGURE 3. Images of different varieties of sorghum grain granules. (a) Japonica sorghum grain sample; (b) glutinous sorghum grain sample.

variations in shape and color for different perspectives, the vibration can also change the upward facing surface of the granules, thus enhancing data coverage, improving sampling efficiency and helping to increase the accuracy of the trained model.

B. IMAGE PROCESSING

Experienced workers are able to determine japonica sorghum and glutinous sorghum by eyes, as shown in Fig. 3, the color of japonica sorghum is yellowish and dull, and the color of glutinous sorghum is reddish and shiny. However, we can also see from Fig. 3 that the differences within the same sorghum variety is not much less than the differences between varieties.

It is quite difficult to identify the adulteration in the sorghum granules when they are piled up together. For industrial practice, an easy-to-implement method is to photograph the granules scattered on the conveyor belt, detect and classify each grain, and calculate the adulteration ratio by

$$R = \frac{N_{ad}}{N} \times 100\% \tag{1}$$

where, R is the adulteration ratio, N_{ad} is the number of adulterated particles in the sample, and N is the total number of sorghum particles in the sample.

Using related functions in MATLAB Image Processing Toolbox or OpenCV, we could segment individual granule from the aforementioned images [11]. The specific processing flow is as follows, and the results of each step are shown as Fig. 4:

1) Brightness equalization. When taking pictures to acquire images, the uneven illumination caused shadows in the background, which will affect the edge detection effect and also lead to differences in the histogram distribution of color space between segmented images, reducing the data uniformity. Hence, it is necessary to identify and subtract the background, and adjust the image to equalize the brightness.
2) Edge detection. Convert the image to grayscale, use low-pass filtering methods such as Gaussian blur to remove the image noise. Take morphological operations like erode and dilate to separate adjoint sorghum grains. Then find the outside contours of

each connected component using the Canny edge detector [12]. The corresponding low and high thresholds for gray scale gradient are 100 and 200 respectively.

3) Image segmentation. Approximate the contours with polygons using Douglas–Peucker algorithm [13]. Calculate the minimal up-right bounding rectangle of each polygon, manually set thresholds for width and height to filter noise points, which was set as width multiply height no less than 1700 pixel^2 in practice. To preserve the size information of the grains, we used square with fixed side length (140 pixels) to segment each granule. The square has the same center as the bounding rectangle, and its side length is larger than the maximum value among the long sides of the rectangles.

C. DEEP NEURAL NETWORK BASED CLASSIFICATION

In this project, the inputs to the deep neural network are pictures, so we chose models using convolutional neural network structure (CNN) as the classifiers. This kind of network structure was inspired by the principles of human vision which recognizes different objects in a hierarchical manner, thus being suitable for processing image information [14], [15]. One of the biggest advantages of CNN is that the so-called feature selection engineering can automatically implemented. That is to say, it is not necessary to prepare and extract the features such as particles shape, size distribution, and different color histograms including RGB, HSV and CIELAB from sorghum images [10]. In our experiments, we mainly used two derivative networks of CNN, i.e., ResNet and SqueezeNet.

ResNet was proposed by He et al., who discovered the degradation phenomenon, and invented the shortcut connection to eliminate the problem of training neural networks with too much depth [16]. The shortcut connection, i.e., residual learning block, uses identity mapping connection that skip multiple layers, the gradient vanishing in the back-propagation process is alleviated. When solving various image tasks, ResNet serves as the default architecture or baselines for years. Recently, Wightman *et al.* found that the network still has unexploited potential through data augmentation and training process optimization [17].

SqueezeNet is a lightweight and efficient CNN model proposed by Han *et al.* It achieves the model performance accuracy close to AlexNet, but has 50x fewer parameters than the latter [18], [19]. The core idea of SqueezeNet is the Fire module, which consisting of squeeze layer and expand layer. The practice in the Fire module that replacing 3x3 convolution filter with 1x1 ones and decreasing input channels to 3x3 filters streamline the number of parameters. With acceptable performance, this model has faster computing speed and is easy for deployment on low-cost hardware, making it competent for industrial field applications.

We used adaptive global average pooling and log softmax at the end of the networks, then employ negative log likelihood (nll) loss, the calculation of log softmax and nll loss are as follow

$$log\ softmax(x_{ij}) = \ln\left(\frac{e^{x_{ij}}}{\sum_{k=1}^{C} e^{x_{ik}}}\right) \tag{2}$$

$$nll\ loss = -\frac{1}{N}\sum_{i=1}^{N} logsoftmax(x_{iy_i}) \tag{3}$$

where C is the number of classes, N is the batch size, y_i is the class of the i-th sample.

TABLE 1. Dataset size.

Sorghum variety	Train set	Validation set	Test set	Total
Japonica	19298	5514	2757	28547
glutinous	20132	5752	2876	28760

III. RESULTS AND DISCUSSION

A. DATA PREPARATION

The raw videos were shoot at 80 frames per second while the vibration base working frequency is 50 Hz, amplitude is 5 mm. We captured 534 images for japonica sorghum and 529 for glutinous sorghum. After image segmentation, we obtained 28574 and 28760 images with the size of 56×56 for the two varieties of sorghum granules respectively, then divided them into the train, validation, test sets according to the ratio of 7:2:1. Table I shows the detailed size of the dataset.

B. CLASSIFIER TRAINING

Since we were to solve a binary classification task and the amount of data was not too large, we chose to train the relatively simple models ResNet-18 and SqueezeNet v1.1 using an NVIDIA GTX 1080ti. We employed the Adadelta optimizer [20], started the training with an initial learning rate of 10^{-3} and applied a step scheduler with a step-size of 15 and $\gamma = 0.7$. The training duration of ResNet-18 and SqueezeNet v1.1 are 5 hours 59 minutes and 6 hours 27 minutes respectively.

To verify the reliability and performance of the deep neural network based method for distinguishing japonica sorghum and glutinous sorghum, the results from the support vector machine (SVM) based method in our previous work were used as baseline for comparison [10]. We extracted particle morphological and color features including area, major and minor axis length, eccentricity, roundness, shape factor, aspect ratio, RGB, HSV and CIELAB statistics from the segmented images [21]. Then we implemented normalization and principal component analysis (PCA) for data dimension reduction. The selected vectors by PCA were taken as the input for SVM. We used libsvm and selected radial basis function (RBF) kernel for model training [22].

Fig. 5 shows the training loss, validation loss and validation accuracy curves from the classifier training process. From the validation loss in first row, it can be found that

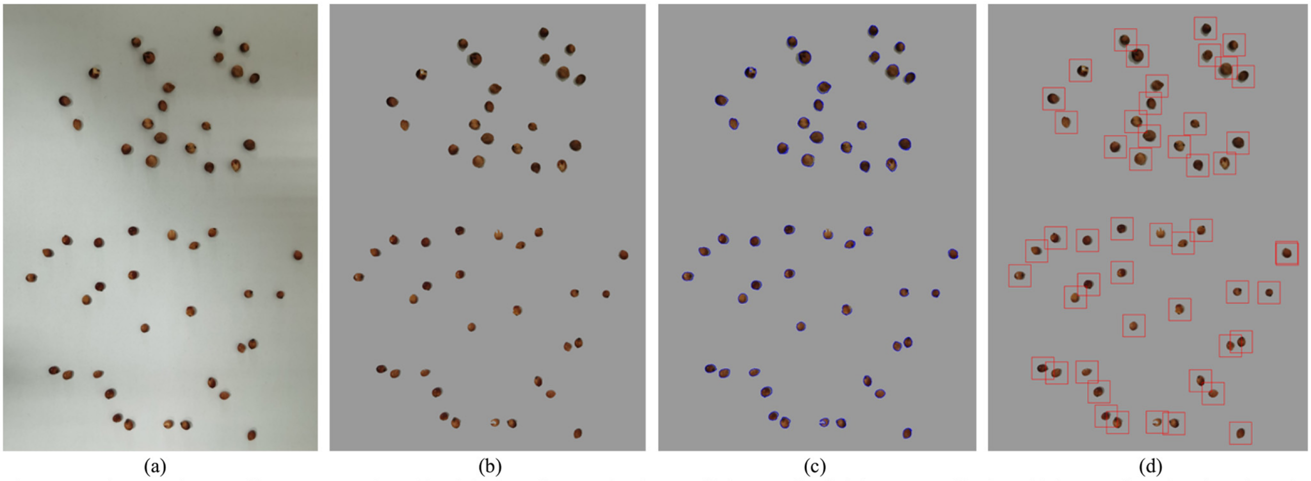


FIGURE 4. Results at each step of image processing. (a) original sorghum grains image; (b) image after brightness equalization; (c) image after edge detection, the contours are marked with blue circles; (d) image after segmentation, the segmented sorghum granules are bounded with red rectangles.

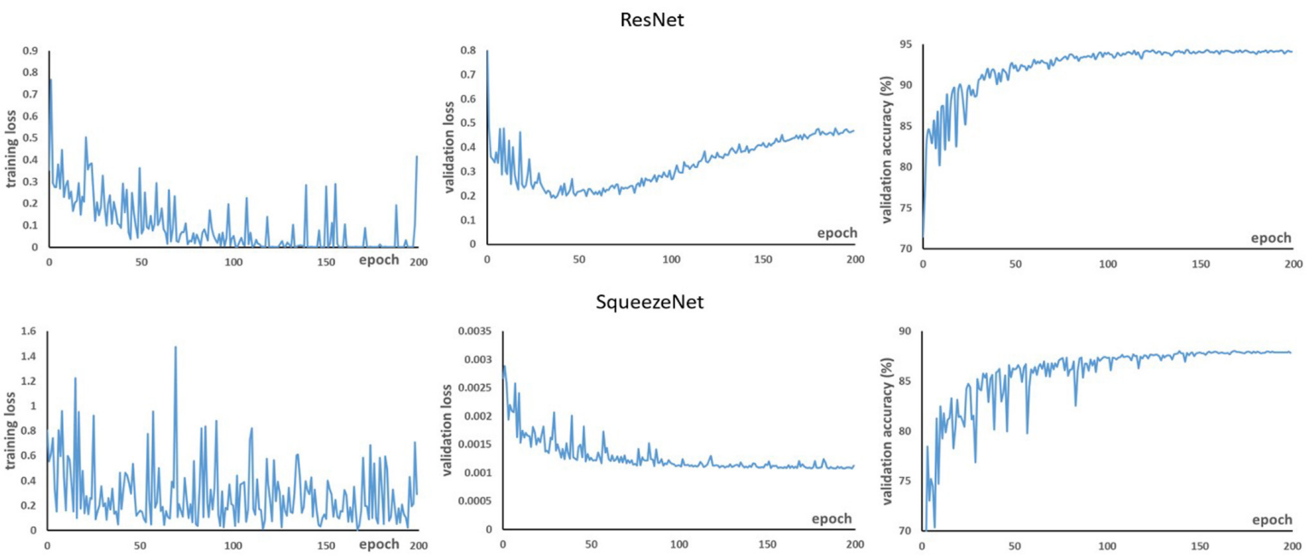


FIGURE 5. Training loss, validation loss and validation accuracy curves of the model training process. The first row is ResNet-18, the second row is SqueezeNet v1.1.

TABLE 2. Model accuracy comparison.

Model	Train set	Validation set	Test set
SVM	-	75.19%	74.92%
ResNet-18	**99.08%**	**93.71%**	**93.34%**
SqueezeNet v1.1	88.77%	87.80%	87.98%

the ResNet-18 model was overfitted after around 60 epochs, whereas for the SqueezeNet v1.1 model, which structure is much simpler, there was no overfitting phenomenon. It is worth noted that the validation loss of SqueezeNet was much smaller than that of ResNet, this may be due to that there is no regularization in SqueezeNet, and the prediction confidence would be close to 1, then the loss obtained by the logarithmic operation would be close to zero.

A comparison of the above model performance is shown in Table II, we can see that ResNet-18 achieved the highest accuracy, while SqueezeNet performed slightly better than SVM, which implies that our proposed method is competent for the discrimination of the two sorghum varieties.

C. ADULTERATION IDENTIFICATION TEST

To evaluate the performance of the proposed deep neural networks-based identification of sorghum varieties and adulteration detection, the adulteration samples were constructed by mixing glutinous sorghums with japonica sorghums at five different levels of 10%, 20%, 30%, 40% and 50%. For each adulteration level, we sampled 14 different batches and took two pictures of each batch, one with the two varieties of sorghum separated and the other with them mixed together. Fig. 6(a) and Fig. 6(b) are the pictures of a certain batch at 20% adulteration ratio.

We used the aforementioned image processing algorithm to segment the particles in each of these 140 images and

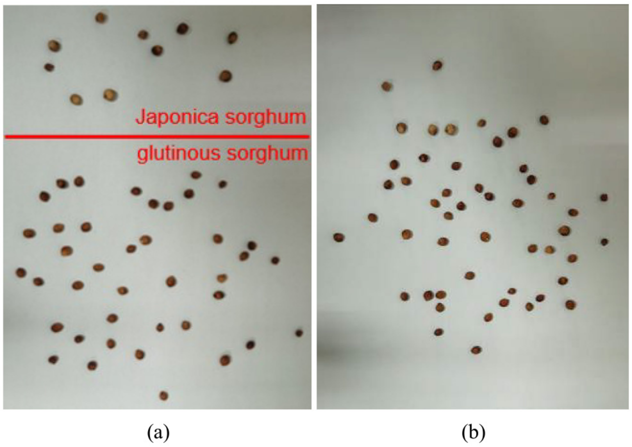


FIGURE 6. Images for adulteration identification test with the number of japonica sorghum grains accounted for 20%. (a) two varieties of sorghum are separate with japonica sorghums on the top; (b) two varieties of sorghum are mixed together.

TABLE 3. Model adulteration test metrics comparison.

Model	RMSE (%)	MAE (%)	R^2 score	Time cost (s)
ResNet-18	**4.95**	**4.20**	**0.878**	0.712
SqueezeNet v1.1	7.73	6.29	0.701	**0.641**

discriminated them using the trained classifiers, then marked two varieties of sorghum with different colored bounding rectangles. Fig. 7 demonstrates the classification result regarding to the images shown in Fig. 6. It is found that the image segmentation algorithm missed certain granules, while the trained models inevitably suffered from misclassification to certain extend.

According to the classification results demonstrated in Fig. 7, the related adulteration ratio can be calculated based on the definition in equation (1), which are 19.61%, 16.00%, 17.65% and 18.60% respectively. By following the same procedure, all 140 images for adulteration detection are evaluated. The statistics of root mean squared error (RSME) and mean absolute error (MAE) are shown in Table 3. Fig. 8 depicts some other test results from the ResNet-18 for the samples with the adulteration ratio at 10%, 30%, 40% and 50%, and the calculated adulteration ratios are 11.11%, 30.61%, 43.75% and 46.94% respectively.

The boxplot of adulteration detection is depicted in Fig. 9. It is found that the R^2 score metrics were not satisfactory enough, which may be mainly owing to the unstable outcome of particle segmentation for different images. Comparing the two deep neural networks detection time cost for single image, the SqueezeNet is relatively faster than the ResNet model, whereas the difference is not quite obvious. This may be due to the image processing accounts for most of the time. The processing time were measured on a 2.50GHz x64 processor E5-2678 v3 and an NVIDIA GTX 1080ti, the test time cost statistics are also given in Table 3.

From the Fig. 8 we can infer that, the primary method to reduce the error is to improve image edge detection algorithm

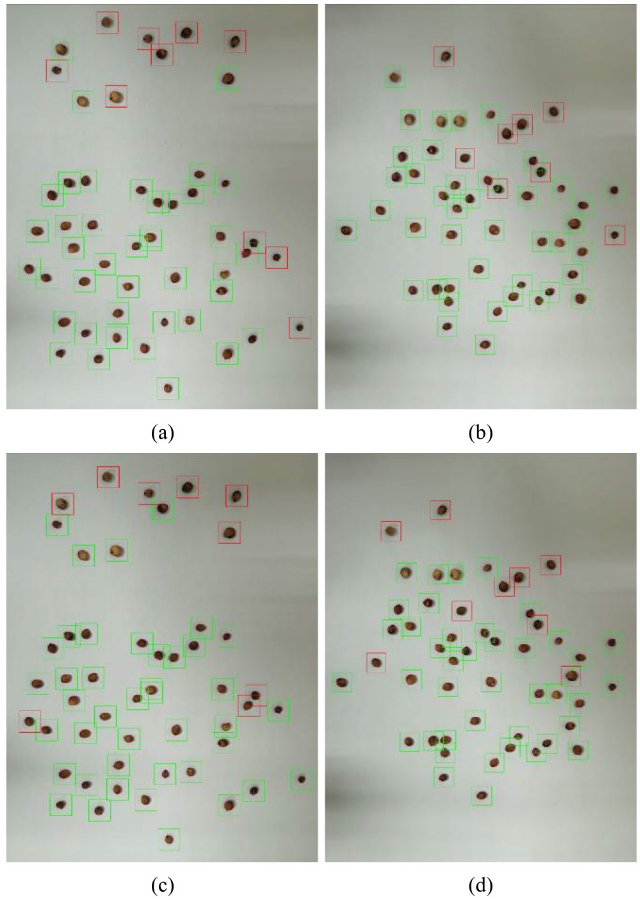


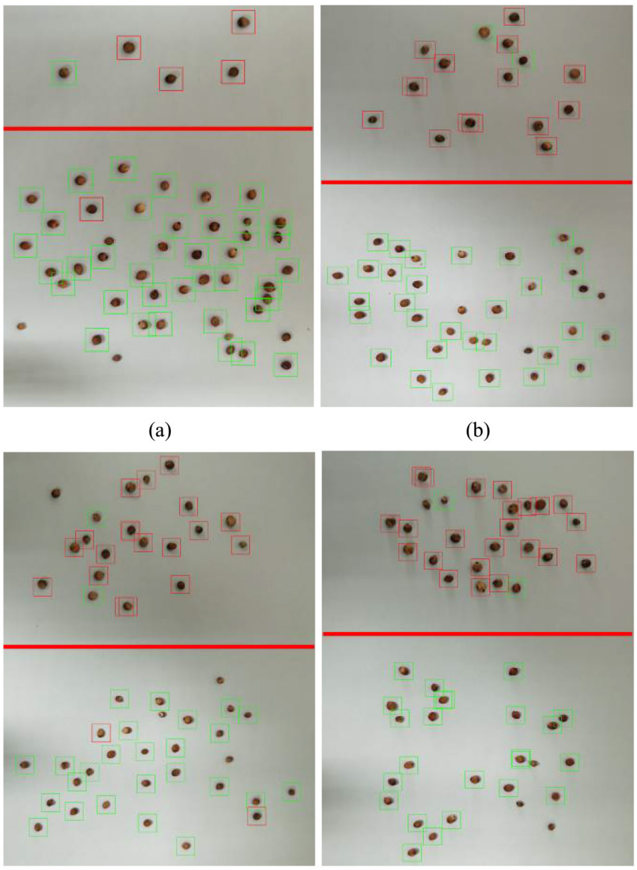
FIGURE 7. Adulteration detection results regarding to Fig. 6. The predicted japonica sorghums are bounded with red boxes, the predicted glutinous sorghums are bounded with green boxes. (a) and (b) are results obtained from ResNet-18, (c) and (d) are from SqueezeNet v1.1.

and avoid bounding boxes overlapping, ensuring the grains are segmented without duplication or omission. In our experiments, the grain segmentation performance was tuned by manually aligning the Canny detector thresholds, blur filter kernel size and other parameters, which is inefficient and holds low generalizability. The subsequent work could apply connected component calculation and non-maximum suppression algorithm.

Secondly, the accuracy of the classifiers should be improved as much as possible, mitigating the effects of Bayes error. This requires the adjustment and design of the corresponding network structure, as well as the careful configuration of training hyperparameters.

D. DISCUSSION

In our adulteration test experiments, we found that the classification results from trained deep learning models were sensitive to the image segmentation square size. This may be due to the differences in the resolution of the cameras used to capture the training dataset and the adulteration test images, as well as the distance from the cameras to the sorghum granules. Therefore, our proposed method requires



(a) (b)

(c) (d)

FIGURE 8. **ResNet-18 adulteration detection results on samples with other adulteration ratio levels. The predicted japonica sorghums are bounded with red boxes, the predicted glutinous sorghums are bounded with green boxes, the glutinous sorghums in ground truth are below the red line in the pictures. (a) japonica sorghums accounted for 10%; (b) 30%; (c) 40%; (d) 50%.**

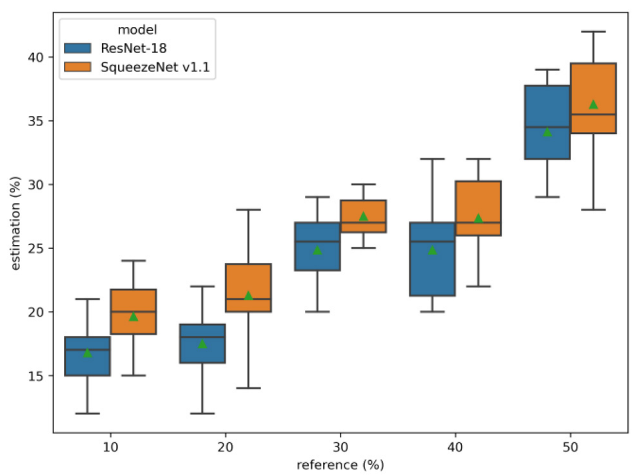


FIGURE 9. **Boxplot of adulteration detection results.**

fine-tuning of the trained model by taking a certain number of labeled images using the camera mounted above the conveyor belt prior to industrial application. Another alternative solution envisioned is to employ normalization and PCA on morphology, color and texture features of individual grains, take the processed features as the input of BPNN (or other machine learning models), which can eliminate the impact of segmentation square size systematically.

In addition, the network structure can be adjusted to further improve sorghum variety classification accuracy by drawing inspiration from related work of fine-grained recognition [23], [24].

Considering the large number of sorghum grains in industrial production, it is difficult to disperse them on the conveyor belt to the extent that they can be easily segmented. Subsequent research can refer to anomaly detection studies to locate anomalous areas in images with dense sorghum particles, qualitatively determine the presence of adulteration and provide some guidance for calculating the adulteration ratio [25]–[27].

IV. CONCLUSION

We demonstrated a novel deep neural network based adulteration detection pipeline for sorghum varieties in Baijiu brewing process. We collected the dataset using a set of devices consisting of vibration base and CMOS camera. We segmented individual grains from the raw images and fed into networks. Compared to the performance of SVM using sorghum grain morphological and color feature vectors, the deep neural networks achieved higher accuracy and better generalizability.

The proposed method allows for fast, non-intrusive and low-cost adulteration detection of brewing materials, and has the prospect of promoting the automation of brewing industries and improving production efficiency.

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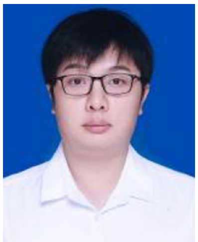

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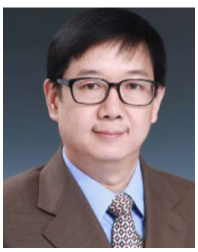

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