Normal and Peaberry Coffee Beans Classification from Green Coffee Bean Images Using Convolutional Neural Networks and Support Vector Machine

Hira Lal Gope, Hidekazu Fukai

Abstract—The aim of this study is to develop a system which can identify and sort peaberries automatically at low cost for coffee producers in developing countries. In this paper, the focus is on the classification of peaberries and normal coffee beans using image processing and machine learning techniques. The peaberry is not bad and not a normal bean. The peaberry is born in an only single seed, relatively round seed from a coffee cherry instead of the usual flat-sided pair of beans. It has another value and flavor. To make the taste of the coffee better, it is necessary to separate the peaberry and normal bean before green coffee beans roasting. Otherwise, the taste of total beans will be mixed, and it will be bad. In roaster procedure time, all the beans shape, size, and weight must be unique; otherwise, the larger bean will take more time for roasting inside. The peaberry has a different size and different shape even though they have the same weight as normal beans. The peaberry roasts slower than other normal beans. Therefore, neither technique provides a good option to select the peaberries. Defect beans, e.g., sour, broken, black, and fade bean, are easy to check and pick up manually by hand. On the other hand, the peaberry pick up is very difficult even for trained specialists because the shape and color of the peaberry are similar to normal beans. In this study, we use image processing and machine learning techniques to discriminate the normal and peaberry bean as a part of the sorting system. As the first step, we applied Deep Convolutional Neural Networks (CNN) and Support Vector Machine (SVM) as machine learning techniques to discriminate the peaberry and normal bean. As a result, better performance was obtained with CNN than with SVM for the discrimination of the peaberry. The trained artificial neural network with high performance CPU and GPU in this work will be simply installed into the inexpensive and low in calculation Raspberry Pi system. We assume that this system will be used in under developed countries. The study evaluates and compares the feasibility of the methods in terms of accuracy of classification and processing speed.

Keywords—Convolutional neural networks, coffee bean, peaberry, sorting, support vector machine.

I. INTRODUCTION

IN the world markets, every day more than two billion cups of coffee are consumed, which makes coffee one of the most popular beverages and over the years, coffee consumption and the demand for high-quality coffee beans have been increasing [1], [2]. The coffee grows in the tropics and is one of the most important crops to earn foreign currency for several under developing countries. Evaluating

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the green coffee beans quality is an important issue for competitive market price, general consumer acceptance and storage stability for the developing countries [4].

The peaberry is a round bean bearing one bean instead of the usual flat-sided bean pair (shown in Fig. 1 (b)) [28]. The peaberries visible features would be the size and shape as compared to normal coffee beans [7]. The peaberry coffee is very limited, with only around 7% of any given coffee crop being peaberries [6], [11]. The peaberries are not specific to any particular region and can grow anywhere [12]. Out of the total production, the peaberry is often hand-selected by farmers and the defect beans are also removed by hand [5]. Picking up the peaberry is more complicated and time-consuming than defect beans. The higher price for the peaberry beans arises from their reportedly higher concentrated flavor compared to normal beans [6], [11].

The peaberry coffee is one of the expensive coffee specialties in the world. The peaberry (also called '*kopi lanang*' in Indonesian and caracol or snail in Spanish) is a natural coffee bean mutation within the coffee cherry [6], [11]. To meet the consumer's quality requirements, peaberry specialty coffee authentication is also one of the major challenges that have become increasingly important in the coffee trade as a result of the significant increase in the price gap between the peaberry and normal coffee in recent years [11]. On coffee beans roast, besides size uniformity, the uniformity of shape is also preferred for roast uniformity; thus, the peaberry should be separated [9]. Peaberries are considered an anomaly and often separated from the green coffee bean, commanding a higher value in most instances [8].

Image classification technology is a rapidly growing area of informatics. In the world, there are various algorithms used for classification. In the image processing field, incidentally, the presence of the technique of deep CNN has been especially increased because of their powerful performances and availabilities for wide applications. Deep neural networks allow computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction [15]. These methods have significantly improved the performance of speech recognition, object detection, visual object recognition and many other domains, including drug discovery and genomics [34].

In general, the main inspiration behind the application of image analysis or computer vision systems to agricultural products is due to the drawbacks of manual classification and grading systems such as subjectivity, tediousness, labor

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requirements, cost, and inconsistency, as many researchers have reported [16]-[27]. The peaberry beans of special type roast more slowly than other normal beans. Coffee beans were detected and selected using various techniques [6]. Therefore, neither technique provides a good option to select the peaberries, meaning a more modern approach is needed [4]. The identification and selection of the peaberries need a robust and easy process.

The novelty of this study is to develop an automatic normal and peaberry coffee bean identification and selection system, which can estimate the accuracy of normal and peaberry coffee beans using deep CNN, a state-of-art technique of the image processing field [10]. We developed a computer program as the first step, whose input is a color image of a green coffee bean and the output is the probability of each bean category.

In this research, we also applied the conventional SVM with a linear kernel for the classification and compared the performances of CNN and SVM in terms of classification accuracy [9]. We will install Raspberry Pi on desktop PC with a tiny affordable single-board computing module. On Raspberry Pi, we will be implementing the coffee bean classifier for training the CNN models. Python (a programing language), Chainer (an open source library of neural networks for deep learning), and OpenCV (an open source library for computer vision) will be installed on Raspberry Pi. We will develop a python program that uses a camera module to take a photo of a green coffee bean, converts the photo image with OpenCV to fit the image as a CNN input, and then classify the coffee bean images using CNN with network pre-trained parameters. We will estimate the classifier's performance on two types of normal and the peaberry binary classification from green coffee bean images [9].

II. MATERIALS AND METHODS

A. Normal and the Peaberry Coffee

1. *Normal Coffee Bean:* Normal coffee beans have no defects, and it is not a defect type. From a coffee cherry, this type of bean contains two beans with their flat sides together like the two halves of a peanut (Fig. 1 (a)) [6], [11].
2. *Peaberry Coffee Bean:* The special type of the peaberry coffee seed is born in only one of the two seeds, a relatively round seed from a coffee cherry instead of the normal flat-sided seed pair (Fig. 1 (b)).

B. Process of Normal and the Peaberry Coffee Bean Images

The important features in the selection process are physical appearance including color, morphology, shape, and size [3]. Fig. 2 shows the sequence of coffee bean image classification and its analysis. The research aim is to develop an automatic sorting system with good accuracy. The procedure of our image classification algorithms is:
1. Digital image finding from image dataset.
2. Principle Component Analysis (PCA) for feature extraction.

3. When we applied classification algorithms on normal and peaberry coffee bean image datasets, the accuracy of the individual algorithm emerged.
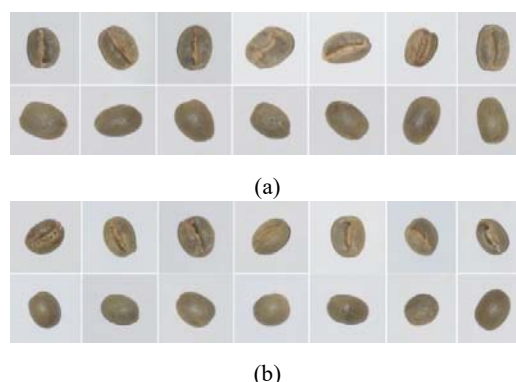

(a)

(b)

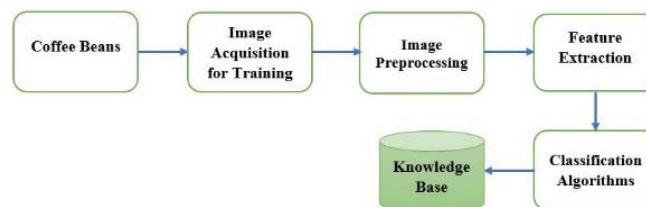Fig. 1 Coffee bean types: (a) normal and (b) peaberry

Fig. 2 Block diagram of coffee bean image processing

C. Image Acquisition

The neural network inputs were digital images of green coffee beans. The coffee bean samples were from Timor-Leste. The green coffee beans were placed onto white paper before taking photographs using a Nikon digital camera. The camera was set with F/16 f-number, exposure time 1/60 s, ISO 200, exposure compensation 1.3, and autofocus mode set to automatic mode. The camera was placed at 1 m above from the bean's surface. Both the front and back sides of the beans were photographed. To ensure the brightness around the subject was uniform, three lighting devices were placed around the beans [9]. The shooting environment is shown in Figs. 3 and 4. Image preprocessing techniques were applied to the photographs to isolate each bean (Fig. 5). About 3,338 samples of the normal and the peaberry were prepared. The size of each image was set to 32×32 pixels, 64×64 pixels, 128×128 pixels and 256×256 pixels. The images were manually labeled as normal and peaberry. Note that one image may have multiple labels [9], [10].

To apply the machine learning techniques, all the sample images were divided into three groups: training data, validation data and test data. The training data were used for training the machine learning models. The validation data were used to confirm the transition of classification performance during the neural networks training phase. The test data were used to evaluate the ability of the trained models to sort with final parameters. The number of images for each group is shown in Table I.

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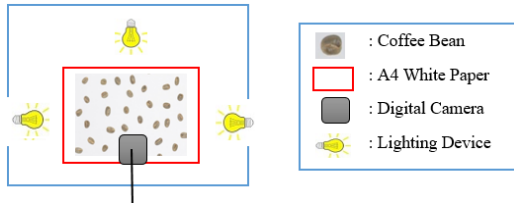Vol:14, No:6, 2020

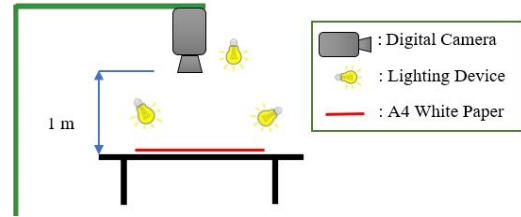Fig. 3 Photographic environment depicted from above

Fig. 4 Photographic environment from the side

Fig. 5 Coffee bean images (1:1) obtained by applying image pre-processing technique [9], [10]

TABLE I
THE NUMBER OF IMAGES FOR EACH TASK

Task	Training	Validation	Test
Normal	1140	570	190
Peaberry	863	431	144

D. CNN

The CNN is a form of artificial neural network that is mainly applied for the recognition of images [14]. CNNs apply to image processing, natural language processing, and other cognitive tasks. ConvNet also is known as a CNN [29]. CNN is consisting of three types of layers (Fig. 6). The convolution layer has the purpose of extracting features of an image using spatial filters. Assume that, input from $(l-1)^{th}$ layer proceeds with a convolutional connection to the lth layer. Let the input take the form of $W \times W \times K$ and the layer of convolution has M spatial filter types in the form of $H \times H \times K$. Then, calculate the output u_{ijm} by convolving this spatial filter on the input as in (1) [9].

$$u_{ijm} = \sum_{k=0}^{K-1}\sum_{p=0}^{H-1}\sum_{q=0}^{H-1} z_{i+p,j+q,\,k}^{(l-1)}\, {}^{h}pqkm + b_{ijm} \quad (1)$$

Here, the b_{ijm} parameter is a bias of the layer. The activation function $f(\cdot)$ is then applied to the u_{ijm} as in (2) and thus, we get $z_{ijm}^{(l)}$ as the output of the convolution layer [9].

$$z_{ijm}^{(l)} = f(u_{ijm}) \quad (2)$$

The output shape changes depending on the filter stride. For instance, if the stride value s is 2, the output of the width and height will be half of the input. A convolution schematics diagram is shown in Fig. 7 [9].

Usually, the pooling layer is positioned just after the convolution layer. The role of the pooling layer is to decrease the sensitivity of the feature to the position, which extracted by the convolution layer, so even if the position of the target feature in the image shifts slightly, the output of the pooling layer does not differ. There are several types of methods for pooling. In this study, max pooling is used. Max pooling is a method that sets the maximum value contained in P_{ij} as an output value u_{ijk}, described as (3) [9].

$$u_{ijk} = \max_{(p,q) \in P_{ij}} z_{pqk} \quad (3)$$

For every channel k, the max pooling is applied independently. The size of output depends on the stride as same as the convolution layer.

The fully connected layer has a role of converging features that are obtained by repeating convolution and pooling to the number of classes we want to classify. This same type of architecture was used in classical artificial neural networks. The fully connected output layer z_j is given by (4) and (5) [9].

$$u_j = \sum_{i=1}^{I} w_{ji}x_i + b_j \quad (4)$$

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Here, the activation function is $f(\cdot)$.

$$z_j = f(u_j) \qquad (5)$$

In this paper, the rectified linear unit (ReLU) function is used for the activation function for the layers of convolution and the fully connected layers. The function ReLU is described as (6) [9].

$$f(x) = \begin{cases} x \ (x > 0) \\ 0 \ (x \le 0) \end{cases} \qquad (6)$$

The sigmoid function is used in the final layer. Generally, the sigmoid function is used to get each unit's output value as the probabilities that the input belongs to each class and the sigmoid function is described as (7) [9].
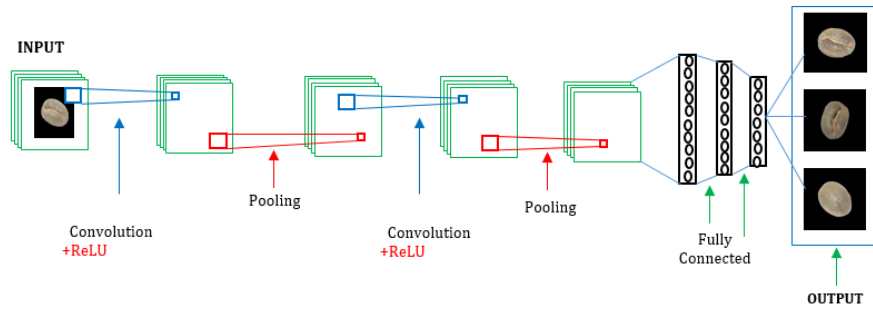
$$f(x) = \frac{1}{1+e^{-x}} \qquad (7)$$

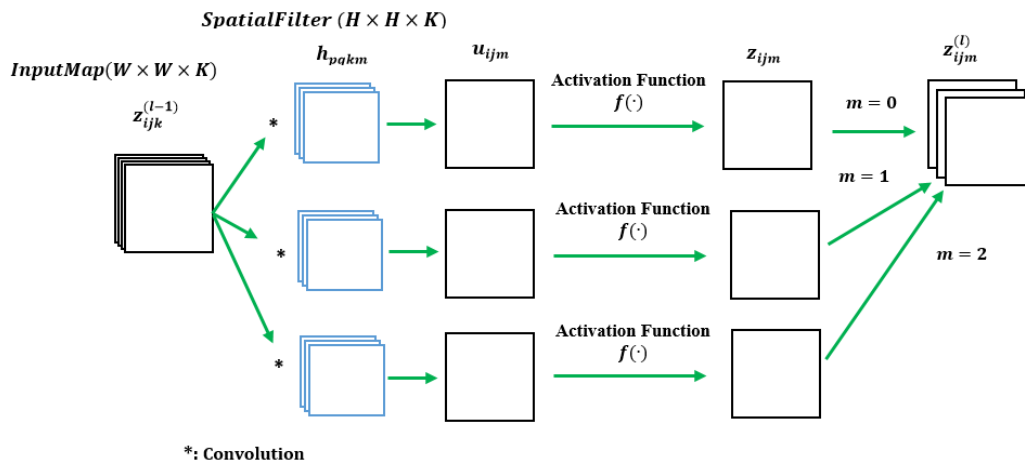Fig. 6 The basic structure of a CNN [9], [10]

Fig. 7 Schematic diagram of the convolution [9], [10]

E. SVM

SVM uses the kernel function to convert data from input space into a high dimensional feature space in which it searches for a separating hyperplane [30]. SVM is originally a binary classifier that works by identifying the optimal hyperplane and dividing the data points correctly into two classes. There will be an infinite number of hyperplane and SVM will select the hyperplane with maximum margin. Although SVM can classify only with small areas of training, a medium of large training areas is used in this study. This is because such areas of training appear to produce high accuracy classification. Classification is performed by conventional linear SVM with its legend and percentage area for each class [33]. Different function types such as linear, polynomial, RBF and other functions of the kernel are widely used to transform input space into desired function space. It uses linear hyperplane separation to construct a classifier, yet it is not easy to linearly separate some problems in the original input space. However, it can easily transform the original input space into a nonlinear high dimensional feature space, where an optimal linear separating hyperplane is trivial to find [13]. In this paper, the SVM used here is a conventional linear SVM, the training set of features is used as the input to train a conventional linear SVM and the testing set of features is used to obtain image labels for the frame test predict. The accuracy of the classification refers to the ratio of items to be classified as positive when classified as positive, and items to be classified as negative were classified as negative and are expressed by (8):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (8)$$

where, TP and TN are the numbers of true positive and true negative predictions, on the other hand, FP and FN are the

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numbers of the false positive and false negative for the considered class. The overall 97% accuracy of the coffee bean classification indicates that the SVM classification is good.

TABLE II
PARAMETERS OF THE CNN FOR FOUR KINDS OF THE IMAGE DATASET

A. 32×32 IMAGE SIZE

Layer Name	Filter shape ($H \times H \times K$)	Stride (s)	Output map shape ($W \times W \times M$)	Activatin Function $f(\cdot)$
Input	−	−	$32 \times 32 \times 3$	−
Convolution1	$3 \times 3 \times 3$	1	$30 \times 30 \times 32$	ReLU
Pooling1	$2 \times 2 \times 32$	2	$15 \times 15 \times 32$	−
Convolution2	$3 \times 3 \times 32$	1	$15 \times 15 \times 64$	ReLU
Pooling2	$2 \times 2 \times 64$	2	$7 \times 7 \times 64$	−
Convolution3	$3 \times 3 \times 64$	1	$7 \times 7 \times 128$	ReLU
Pooling3	$2 \times 2 \times 128$	2	$3 \times 3 \times 128$	−
Convolution4	$3 \times 3 \times 128$	1	$3 \times 3 \times 256$	ReLU
Pooling4	$2 \times 2 \times 256$	2	$1 \times 1 \times 256$	−
FullConnected1	−	−	512	ReLU
FullConnected2	−	−	1	Sigmoid

B. 64×64 IMAGE SIZE

Layer Name	Filter shape ($H \times H \times K$)	Stride (s)	Output map shape ($W \times W \times M$)	Activatin Function $f(\cdot)$
Input	−	−	$64 \times 64 \times 3$	−
Convolution1	$3 \times 3 \times 3$	1	$62 \times 62 \times 32$	ReLU
Pooling1	$2 \times 2 \times 32$	2	$31 \times 31 \times 32$	−
Convolution2	$3 \times 3 \times 32$	1	$31 \times 31 \times 64$	ReLU
Pooling2	$2 \times 2 \times 64$	2	$15 \times 15 \times 64$	−
Convolution3	$3 \times 3 \times 64$	1	$15 \times 15 \times 128$	ReLU
Pooling3	$2 \times 2 \times 128$	2	$7 \times 7 \times 128$	−
Convolution4	$3 \times 3 \times 128$	1	$7 \times 7 \times 256$	ReLU
Pooling4	$2 \times 2 \times 256$	2	$3 \times 3 \times 256$	−
FullConnected1	−	−	512	ReLU
FullConnected2	−	−	1	Sigmoid

C. 128×128 IMAGE SIZE

Layer Name	Filter shape ($H \times H \times K$)	Stride (s)	Output map shape ($W \times W \times M$)	Activatin Function $f(\cdot)$
Input	−	−	$128 \times 128 \times 3$	−
Convolution1	$3 \times 3 \times 3$	1	$126 \times 126 \times 32$	ReLU
Pooling1	$2 \times 2 \times 32$	2	$63 \times 63 \times 32$	−
Convolution2	$3 \times 3 \times 32$	1	$63 \times 63 \times 64$	ReLU
Pooling2	$2 \times 2 \times 64$	2	$31 \times 31 \times 64$	−
Convolution3	$3 \times 3 \times 64$	1	$31 \times 31 \times 128$	ReLU
Pooling3	$2 \times 2 \times 128$	2	$15 \times 15 \times 128$	−
Convolution4	$3 \times 3 \times 128$	1	$15 \times 15 \times 256$	ReLU
Pooling4	$2 \times 2 \times 256$	2	$7 \times 7 \times 256$	−
FullConnected1	−	−	512	ReLU
FullConnected2	−	−	1	Sigmoid

D. 256×256 IMAGE SIZE

Layer Name	Filter shape ($H \times H \times K$)	Stride (s)	Output map shape ($W \times W \times M$)	Activatin Function $f(\cdot)$
Input	−	−	$256 \times 256 \times 3$	−
Convolution1	$3 \times 3 \times 3$	1	$254 \times 254 \times 32$	ReLU
Pooling1	$2 \times 2 \times 32$	2	$127 \times 127 \times 32$	−
Convolution2	$3 \times 3 \times 32$	1	$127 \times 127 \times 64$	ReLU
Pooling2	$2 \times 2 \times 64$	2	$63 \times 63 \times 64$	−
Convolution3	$3 \times 3 \times 64$	1	$63 \times 63 \times 128$	ReLU
Pooling3	$2 \times 2 \times 128$	2	$31 \times 31 \times 128$	−
Convolution4	$3 \times 3 \times 128$	1	$31 \times 31 \times 256$	ReLU
Pooling4	$2 \times 2 \times 256$	2	$15 \times 15 \times 256$	−
FullConnected1	−	−	512	ReLU
FullConnected2	−	−	1	Sigmoid

The higher row represents the first layer [9], [10]

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III. Experiment

A. Classification of Normal and the Peaberry Coffee Beans Using CNN and Conventional Linear SVM

Normal and peaberry types of coffee beans are labeled as green coffee beans. However, we performed two binary classifications for each type of bean in the case of coffee beans. The number of coffee bean images used for each classification task is shown in Table I. The parameters of CNN are shown in Table II. The layer was added after the 'FullConnected1' layer and set a dropout rate to 0.5 [31]. The deep learning library, Chainer, was used to implement the CNN [32].

Instead of CNN, we also applied conventional linear SVM to compare the performance in classification accuracy. Parameter C was set to 1 and parameter gamma was set to 'auto' when implementing conventional linear SVM. A scikit-learn machine learning library was used for implementing the SVM. In the conventional linear SVM tasks, to adapt to the SVM, the data were reshaped into a one-dimensional vector form.

IV. Results

The two types of binary classifications were performed on desktop computers by both CNN and conventional linear SVM. In this research, the entire training dataset was divided into training, validation and test data format. Table I shows the total number of 1900 samples of normal and 1438 samples of peaberry coffee beans. We prepared four trained CNN models for four kinds of image sizes such as 32×32 pixels, 64×64 pixels, 128×128 pixels and 256×256 pixels to compare the CNN and conventional linear SVM classification accuracies for the normal and peaberry coffee beans. Better accuracies were obtained from CNN than conventional linear SVM in all

types of classification, as shown in Table III and Fig. 8. The image size did not significantly affect the classification accuracies for the CNN and conventional linear SVM. We obtained high accuracies (over 97%) from CNN as the classification of the conventional linear SVM.
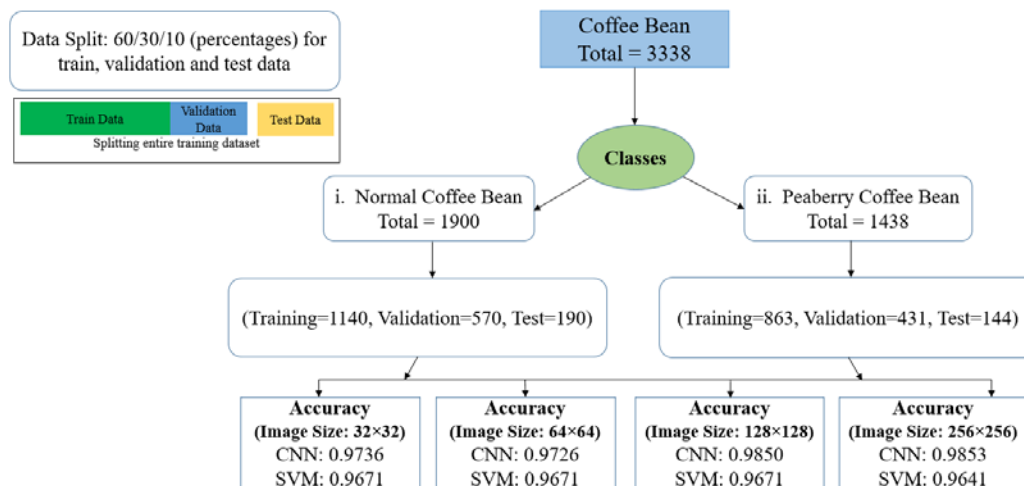
TABLE III
CNN AND SVM ACCURACIES FOR NORMAL AND PEABERRY COFFEE BEAN (FOUR IMAGE SIZES)

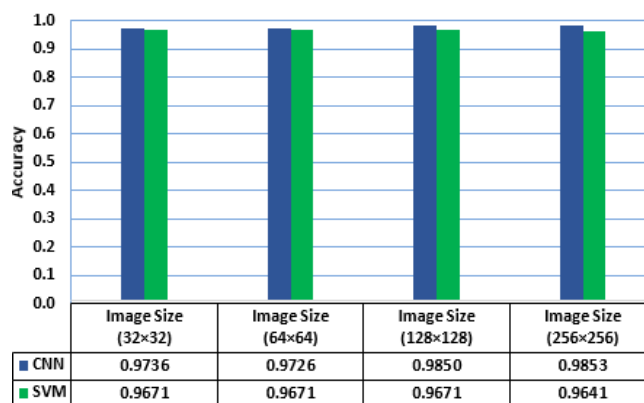| Image Size	Accuracy	
	CNN	SVM with Linear Kernel
32×32	0.9736	0.9671
64×64	0.9726	0.9671
128×128	0.9850	0.9671
256×256	0.9853	0.9641

V. Discussion and Conclusion

As the first step, we discriminate the normal and peaberry coffee beans using CNN of the development of the coffee bean sorting system. Avoiding calculation cost, we used here simple CNN with few convolutional layers. We compared both the CNN results and the conventional linear SVM results. It is confirmed that we obtained better performance with CNN for the discrimination of the peaberry.

The performance could be enhanced by preparing more coffee bean sample images for training, adding more labels for the normal and the peaberry type of coffee bean, using advance SVM kernel level, reconsidering CNN structure or artificial data augmentation by such as random rotation, shifts, and flips. In future research, the trained neural network will be installed simply in the Raspberry Pi system, and we will estimate the feasibility of the sorting system using Raspberry Pi from the point of view of accuracy and data processing time for each image.

(a)

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(b)

Fig. 8 CNN and conventional linear SVM classification accuracies for four kinds of image sizes: (a) flow chart and (b) graphical representation of image data

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