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*Research article*

# Peaberry and normal coffee bean classification using CNN, SVM, and KNN: Their implementation in and the limitations of Raspberry Pi 3

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**Abstract:** Peaberries are a special type of coffee bean with an oval shape. Peaberries are not considered defective, but separating peaberries is important to make the shapes of the remaining beans uniform for roasting evenly. The separation of peaberries and normal coffee beans increases the value of both peaberries and normal coffee beans in the market. However, it is difficult to sort peaberries from normal beans using existing commercial sorting machines because of their similarities. In previous studies, we have shown the availability of image processing and machine learning techniques, such as convolutional neural networks (CNNs), support vector machines (SVMs), and k-nearest-neighbors (KNNs), for the classification of peaberries and normal beans using a powerful desktop PC. As the next step, assuming the use of our system in the least developed countries, this study was performed to examine their implementation in and the limitations of Raspberry Pi 3. To improve the performance, we modified the CNN architecture from our previous studies. As a result, we found that the CNN model outperformed both linear SVM and KNN on the use of Raspberry Pi 3. For instance, the trained CNN could classify approximately 13.77 coffee bean images per second with 98.19% accuracy of the classification with 64×64 pixel color images on Raspberry Pi 3. There were limitations of Raspberry Pi 3 for linear SVM and KNN on the use of large image sizes because of the system's small RAM size. Generally, the linear SVM and KNN were faster than the CNN with small image sizes, but we could not obtain better results with both the linear SVM and KNN than the CNN in terms of the classification accuracy. Our results suggest that the combination of the CNN and Raspberry Pi 3 holds the promise of inexpensive peaberries and a normal bean sorting system for the least developed countries.

**Keywords:** Convolutional Neural Networks (CNN); coffee bean; K-Nearest-Neighbors (KNN); peaberry; Raspberry Pi 3; Support Vector Machine (SVM)

## 1. Introduction

Coffee beans comprise one of the world's most extensively traded agricultural products [1,2]. Brazil, Vietnam, Colombia, and Indonesia earn a large number of foreign currencies, which is vital to their population's livelihood [3,4].

The visible features of peaberries include a diameter smaller than a normal, flat-sided pair of coffee beans, which resemble a football, as they appear to be thicker and more rounded [5]. There are two embryos in a normal coffee cherry, both of which are fertilized and grow inside a confined space, resulting in the typical hemispherical shape of coffee beans. Peaberries occur when only a single embryo is fertilized inside the coffee cherry [6]. Peaberries are limited; approximately 7% of any green coffee crop consists of peaberries [3,7]. Peaberries are not specific to any particular area, and they can grow anywhere [8].

It is important to separate peaberries from normal beans for the following reasons: First, peaberries are often separated to ensure an even roast in high-grade coffee. Because the roasting process significantly affects the taste of coffee and the control of the roasting time depending on bean size is essential, the uniformity of coffee bean size is vital. Even if the beans are sorted by size, separating peaberries is preferred, especially for high-grade coffee, because their shape differs from that of normal beans [9]. Another reason for distinguishing peaberries from normal beans is that the price of a collection of peaberries increases significantly compared to normal beans due to their rarity [7].

Several types of automatic coffee bean sorting machines are already in use in developed countries. The main functions of the sorting machines are to sort the beans by size and/or remove defective beans, such as black, sour, and broken beans, from the normal beans. The machines sort the defects mainly by using color as a clue, so the sorting of peaberries is a hard task for conventional sorting machines because the color of peaberries is similar to the color of normal beans. To the best of our knowledge, there are no automatic sorting machines that can sort peaberries.

Deep learning models have been ubiquitously utilized for image processing. The importance of classification with quality can be noticed in the number of research publications that work with not only neural networks but also simple image processing and other machine learning techniques to sort various vegetables, fruits, crops, beans, etc. The authors used deep learning architecture in the area of tomato crops and found an accuracy of 97.29% and 97.49%, respectively [10]. In another study, the authors used a simple image processing technique in the field of carrot fruit. The classification accuracies of the linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) methods were 92.59% and 96.30%, respectively [11]. The authors applied machine-learning methods such as C4.5 decision tree, logistic regression (LR), support vector machine (SVM), and multilayer perceptron (MLP) for classifying nine major summer crops. The MLP and SVM methods obtained a better accuracy of 88% than LR (86%) and C4.5 (79%) [12]. However, only a few studies have employed deep learning for coffee bean classification. We have been investigating the application of machine learning techniques, including deep learning models, to coffee bean classification. We applied a deep CNN to classify green coffee beans into several defective groups, including peaberries as a class, with accuracies ranging from 72.41% to 98.75% [13]. One limitation of this study was that the number of peaberries used for training was insufficient, resulting in lower accuracy for peaberries. In another study, we examined the availability of Raspberry Pi 3 and a deep CNN method for the classification of several types of defective coffee beans [9]. In our previous study [14], we focused on the sorting of peaberries and normal beans using the CNN on a desktop PC, resulting in accuracies ranging from 97.26% to 98.53% for four different image sizes.

As the next step, this study was performed to examine the implementation of three major machine learning algorithms, e.g., convolutional neural networks (CNNs), support vector machines (SVMs), and k-nearest-neighbors (KNNs), on the Raspberry Pi 3 to classify peaberries and normal beans, assuming the use of our system in the least developed countries. We compared the performances and examined their limitations. In each algorithm, we estimated the calculation time and the accuracy of the classification to verify the availability of Raspberry Pi 3 for classification in practical use.

In the next section, we will describe the materials of peaberries and normal green coffee beans, the experimental setup, and each machine learning method. In Section 3, we describe both the experimental results and the discussion, following the conclusion in Section 4.

## 2. Materials and methods

### *2.1. Green coffee beans*

The collected coffee bean type was Arabica. Dry green coffee bean samples were collected from farmers in Timor-Leste. In this study, two types of green coffee beans are described below:

Peaberry: Peaberries are a single embryo that is fertilized inside coffee cherries instead of the usual flat-sided pair of coffee beans. Peaberries are oval-shaped beans. They are also known as ‘caracol’, ‘perla’, and ‘perle’ [15]. Peaberries tend to be surprisingly acidic with a more intense flavor than normal beans. Peaberries are often hand-selected by farmers from the total harvest and sold as a special grade rather than as normal beans (Figure 1(a)) [3,16].

Normal (no defect): A normal coffee cherry will contain two beans with facing flat sides that are similar to peanut halves (Figure 1(b)) [3,7]. These beans are sometimes referred to as ‘flat beans’. They are perfect and not defective.

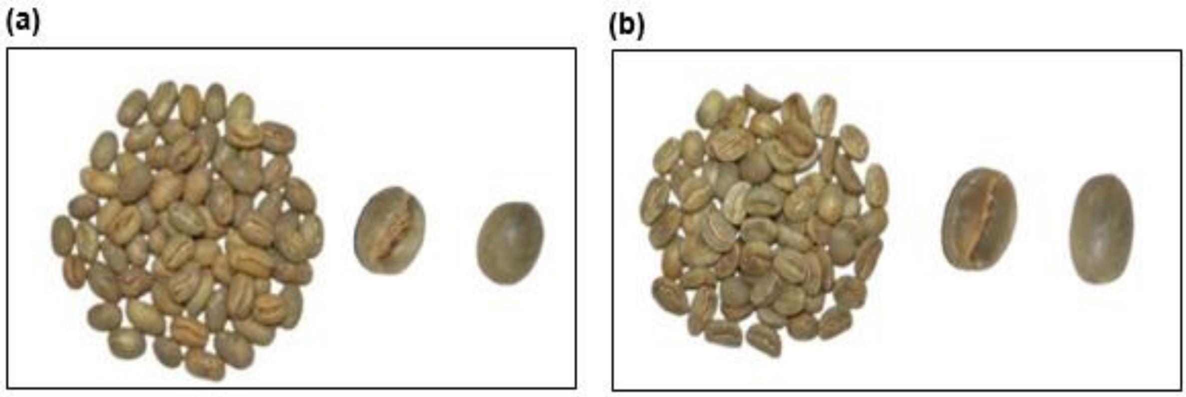



**Figure 1.** Coffee beans: (a) peaberry and (b) normal.

## 2.2. Image acquisition

Peaberries and normal green coffee bean samples were collected from farmers in Timor-Leste. Coffee beans were placed on size A4 white paper, and images were collected with a Nikon digital camera (D5100, Nikon, Tokyo, Japan). The camera parameters were set up as follows: F/16 f-number, exposure time of 1/60 s, ISO 200, exposure compensation of 1.3, autofocus mode, image resolution of 4928 x 3264, and a position of one meter (1 m) above the surface of the beans. Three general lighting devices were employed for the photographic environment, as shown in Figure 2. Both the front-side and back-side of the coffee beans were taken. Then, image sizes were resized to 32 × 32, 64 × 64, 128 × 128, and 256 × 256 pixels, and we also prepared a set of grayscale images with the same size. As the image preprocessing, we applied resizing and grayscale conversion using OpenCV, Open Source Computer Vision Library.

Although the input of CNN, SVM, and KNN can be the features of images extracted by preliminary image processing, we used raw pixel values of images as the input of each CNN, SVM, and KNN in this work. We can expect the network layers of the CNN will extract the features, such as shape, colors, and textures automatically. Also, SVM and KNN accept raw pixel values of images as input for classification.

The objective to prepare several sizes of images for each color and grayscale was to examine the best size of images for the Raspberry Pi 3. The larger image size has more pixel information than a smaller image (Figure 3(a), (b)), and makes the accuracy of the classification higher, whereas the smaller image size makes the processing speed faster.

The images were manually labeled as peaberries and normal coffee beans. All images of the coffee beans were divided into three groups: training data, validation data, and test data. In the neural network training phase, the validation data were utilized to confirm the transition of the classification accuracy. The test data were applied to measure the accuracy (Section 2.7) of the neural networks' sorting ability. Table 1 represents the total number of images for each group.

**Figure 2.** Photographic environment.

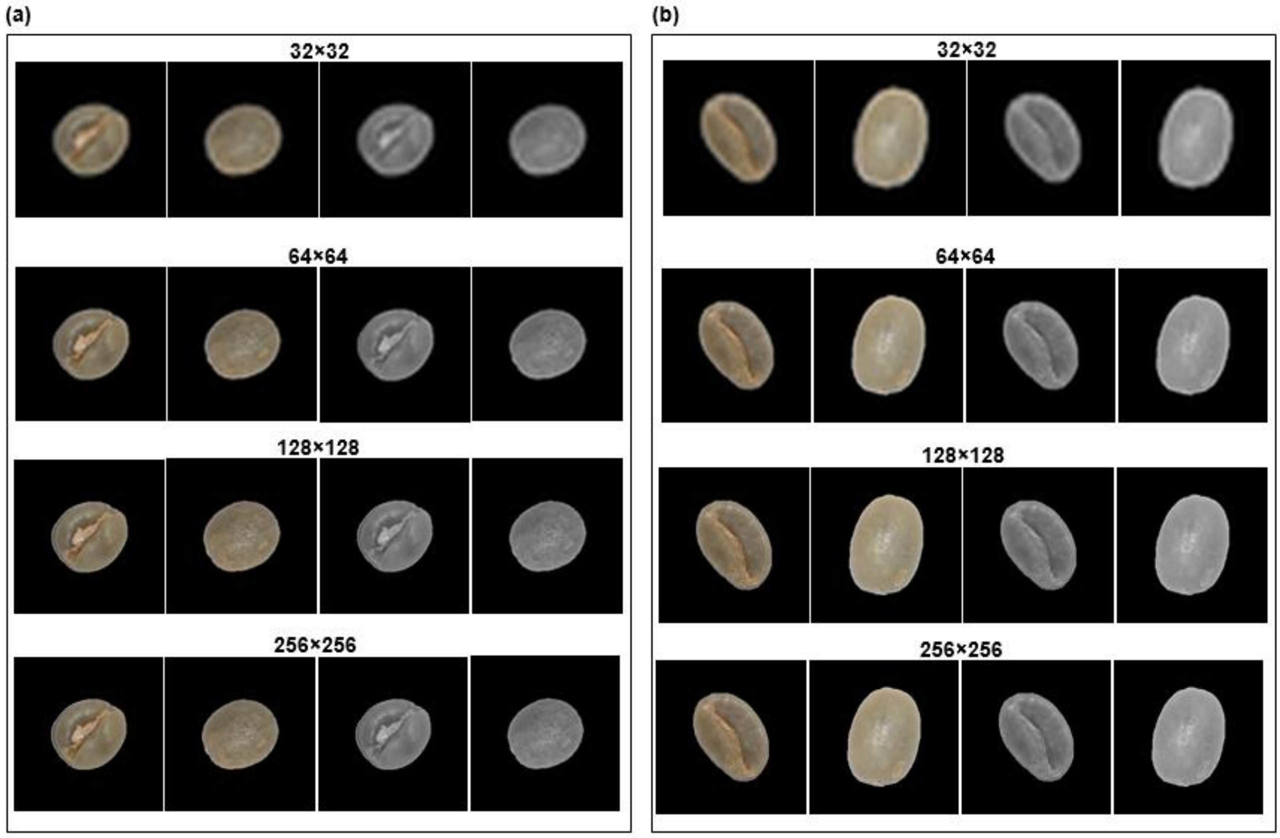



**Figure 3.** Sample images of coffee bean: (a) peaberry and (b) normal bean in color (left side) and grayscale (right side).

**Table 1.** Number of images for each task.

| Task | Training | Validation | Test | Total |
|---|---|---|---|---|
| Peaberry (color) | 1144 | 143 | 143 | 1430 |
| Peaberry (grayscale) | 1144 | 143 | 143 | 1430 |
| Normal (color) | 1520 | 190 | 190 | 1900 |
| Normal (grayscale) | 1520 | 190 | 190 | 1900 |

### *2.3. Convolutional neural networks*

Convolutional neural networks (CNNs) are a form of an artificial neural network; these techniques have dramatically improved the performance of image recognition, object detection, speech recognition, natural language processing, drug discovery and genomics, and many other domains [17–19]. The basic CNN architecture consists of three types of layers: convolutional, pooling, and fully connected layers.

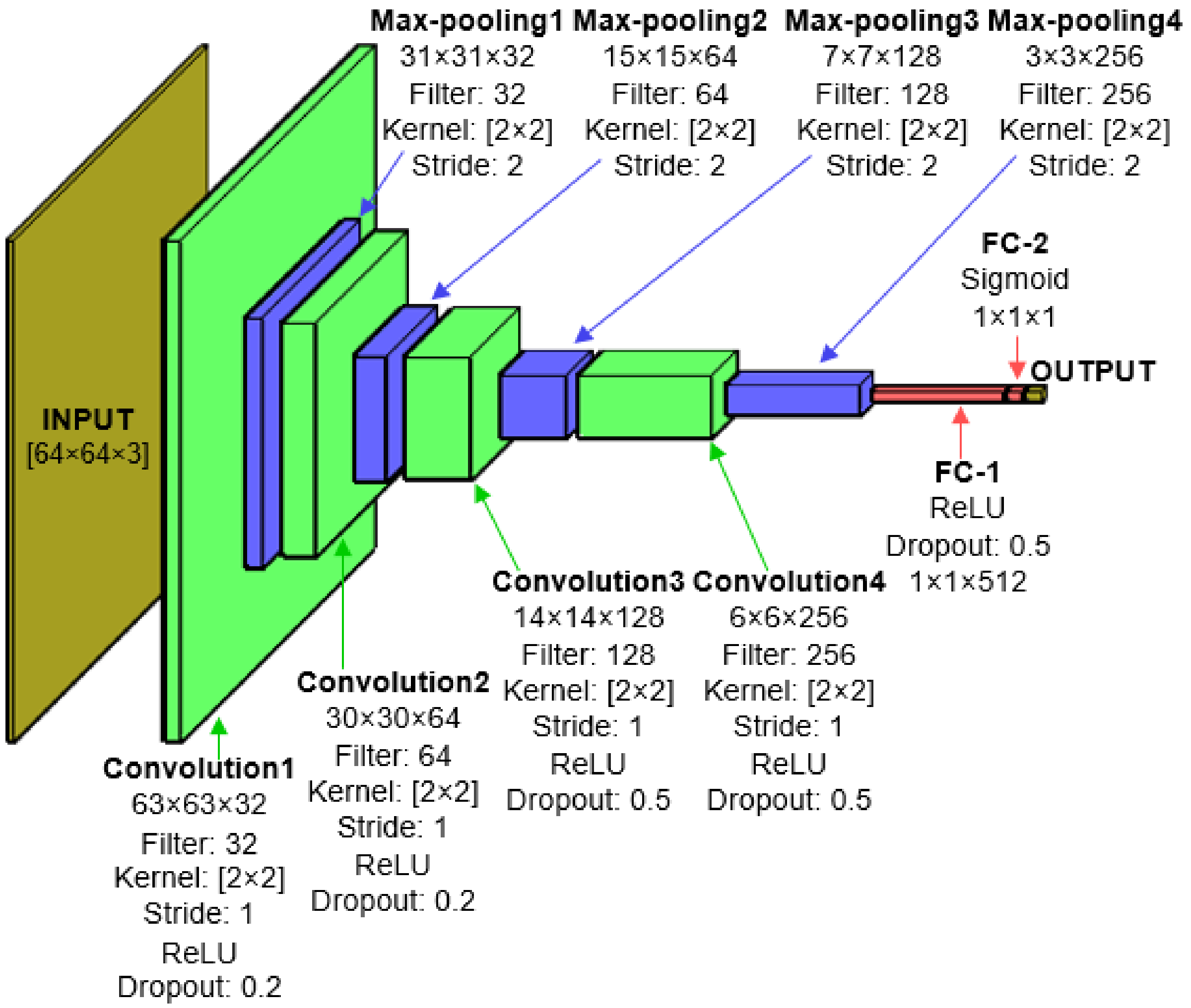



**Figure 4.** Proposed structure of the CNN model for a 64 × 64 color image: four convolutional layers, four max-pooling layers, and two fully connected layers.

Table 2 describes the specifications of the CNN model in this study for 32 × 32, 64 × 64, 128 × 128, and 256 × 256 input image sizes. The structure of the model for 64×64 is described in Figure 4. All the models were written by using Python libraries, such as Keras, TensorFlow, and Numpy. All the proposed CNN models consist of four convolutional layers, and each is followed by a max-pooling layer. The first convolutional layer uses 32 filters and is followed by 64, 128, and 256 filters. Each convolutional layer has a 2 × 2 receptive field that is applied with a stride of 1 pixel. Each max-pooling layer has 2 × 2 regions at a stride of 2 pixels. The Rectified Linear Unit (ReLU) activation function is applied consecutively to each convolutional layer. The last convolutional layer is followed by two fully connected (FC) hidden layers. The two FC layers (FC-1 and FC-2) are employed to increase the performance of the neural network [20,21]. We applied dropout (0.2, 0.2, 0.5, 0.5, and 0.5) in the four convolutional layers and the FC-1 layer to prevent overfitting in the network [22].

The proposed CNN model was tuned with different batch sizes (8, 16, 32), epochs (50, 60, 100), optimizer (SGD, Adam), activation function ('relu' and 'tanh'), and learning rate (0.01, 0.001). We found the best performance for the following conditions: 32 batch size, 100 epochs, SGD (Stochastic Gradient Descent) optimizer, relu activation function, and 0.01 learning rate. The sigmoid function yields a value between 0 and 1, and the output is generally interpreted as a probability on neural networks. After the calculation of the probability of peaberry class using the sigmoid function, we classified the input image of a bean as the peaberry if the probability is more than 0.5 as a threshold value.

**Table 2.** Parameters of CNN for four kinds of image datasets.

| *(a) 32 × 32 image size* | | | | |
|---|---|---|---|---|
| Layer name | Filter shape (H × H × K) | Stride (s) | Output map shape (W × W × M) | Activation function f(·) |
| Input | - | - | 32 × 32 × 3 | - |
| Convolution1 | 2 × 2 × 3 | 1 | 31 × 31 × 32 | ReLU |
| Max-Pooling1 | 2 × 2 × 32 | 2 | 15 × 15 × 32 | - |
| Dropout (0.2) | - | - | 15 × 15 × 32 | - |
| Convolution2 | 2 × 2 × 32 | 1 | 14 × 14 × 64 | ReLU |
| Max-Pooling2 | 2 × 2 × 64 | 2 | 7 × 7 × 64 | - |
| Dropout (0.2) | - | - | 7 × 7 × 64 | - |
| Convolution3 | 2 × 2 × 64 | 1 | 6 × 6 × 128 | ReLU |
| Max-Pooling3 | 2 × 2 × 128 | 2 | 3 × 3 × 128 | - |
| Dropout (0.5) | - | - | 3 × 3 × 128 | - |
| Convolution4 | 2 × 2 × 128 | 1 | 2 × 2 × 256 | ReLU |
| Max-Pooling4 | 2 × 2 × 256 | 2 | 1 × 1 × 256 | - |
| Dropout (0.5) | - | - | 1 × 1 × 256 | - |
| FullConnected1 | - | - | 1 × 1 × 512 | ReLU |
| Dropout (0.5) | - | - | 1 × 1 × 512 | - |
| FullConnected2 | - | - | 1 × 1 × 1 | Sigmoid |
| *(b) 64 × 64 image size* | | | | |
| Input | - | - | 64 × 64 × 3 | - |
| Convolution1 | 2 × 2 × 3 | 1 | 63 × 63 × 32 | ReLU |
| Max-Pooling1 | 2 × 2 × 32 | 2 | 31 × 31 × 32 | - |
| Dropout (0.2) | - | - | 31 × 31 × 32 | - |
| Convolution2 | 2 × 2 × 32 | 1 | 30 × 30 × 64 | ReLU |
| Max-Pooling2 | 2 × 2 × 64 | 2 | 15 × 15 × 64 | - |
| Dropout (0.2) | - | - | 15 × 15 × 64 | - |
| Convolution3 | 2 × 2 × 64 | 1 | 14 × 14 × 128 | ReLU |
| Max-Pooling3 | 2 × 2 × 128 | 2 | 7 × 7 × 128 | - |
| Dropout (0.5) | - | - | 7 × 7 × 128 | - |
| Convolution4 | 2 × 2 × 128 | 1 | 6 × 6 × 256 | ReLU |
| Max-Pooling4 | 2 × 2 × 256 | 2 | 3 × 3 × 256 | - |
| Dropout (0.5) | - | - | 3 × 3 × 256 | - |
| FullConnected1 | - | - | 1 × 1 × 512 | ReLU |
| Dropout (0.5) | - | - | 1 × 1 × 512 | - |
| FullConnected2 | - | - | 1 × 1 × 1 | Sigmoid |

*Continued on the next page*

| Layer name | Filter shape (H × H × K) | Stride (s) | Output map shape (W × W × M) | Activation function f(·) |
|---|---|---|---|---|
| *(c) 128 × 128 image size* | | | | |
| Input | - | - | 128 × 128 × 3 | - |
| Convolution1 | 2 × 2 × 3 | 1 | 127 × 127 × 32 | ReLU |
| Max-Pooling1 | 2 × 2 × 32 | 2 | 63 × 63 × 32 | - |
| Dropout (0.2) | - | - | 63 × 63 × 32 | - |
| Convolution2 | 2 × 2 × 32 | 1 | 62 × 62 × 64 | ReLU |
| Max-Pooling2 | 2 × 2 × 64 | 2 | 31 × 31 × 64 | - |
| Dropout (0.2) | - | - | 31 × 31 × 64 | - |
| Convolution3 | 2 × 2 × 64 | 1 | 30 × 30 × 128 | ReLU |
| Max-Pooling3 | 2 × 2 × 128 | 2 | 15 × 15 × 128 | - |
| Dropout (0.5) | - | - | 15 × 15 × 128 | - |
| Convolution4 | 2 × 2 × 128 | 1 | 14 × 14 × 256 | ReLU |
| Max-Pooling4 | 2 × 2 × 256 | 2 | 7 × 7 × 256 | - |
| Dropout (0.5) | - | - | 7 × 7 × 256 | - |
| FullConnected1 | - | - | 1 × 1 × 512 | ReLU |
| Dropout (0.5) | - | - | 1 × 1 × 512 | - |
| FullConnected2 | - | - | 1 × 1 × 1 | Sigmoid |
| (d) 256×256 image size | | | | |
| Input | - | - | 256 × 256 × 3 | - |
| Convolution1 | 2 × 2 × 3 | 1 | 255 × 255 × 32 | ReLU |
| Max-Pooling1 | 2 × 2 × 32 | 2 | 127 × 127 × 32 | - |
| Dropout (0.2) | - | - | 127 × 127 × 32 | - |
| Convolution2 | 2 × 2 × 32 | 1 | 126 × 126 × 64 | ReLU |
| Max-Pooling2 | 2 × 2 × 64 | 2 | 63 × 63 × 64 | - |
| Dropout (0.2) | - | - | 63 × 63 × 64 | - |
| Convolution3 | 2 × 2 × 64 | 1 | 62 × 62 × 128 | ReLU |
| Max-Pooling3 | 2 × 2 × 128 | 2 | 31 × 31 × 128 | - |
| Dropout (0.5) | - | - | 31 × 31 × 128 | - |
| Convolution4 | 2 × 2 × 128 | 1 | 30 × 30 × 256 | ReLU |
| Max-Pooling4 | 2 × 2 × 256 | 2 | 15 × 15 × 256 | - |
| Dropout (0.5) | - | - | 15 × 15 × 256 | - |
| FullConnected1 | - | - | 1 × 1 × 512 | ReLU |
| Dropout (0.5) | - | - | 1 × 1 × 512 | - |
| FullConnected2 | - | - | 1 × 1 × 1 | Sigmoid |

### *2.4. Visual Geometry Group (VGG-16)*

The VGG-16 is a very simple, straightforward architecture. The number 16 in the name VGG refers to the fact that it is 16 layers deep neural network. Each VGG block consists of a sequence of convolutional layers, which are followed by a max-pooling layer. VGG-16 is composed of 13 convolutional layers, 5 max-pooling layers, and 3 fully connected layers. The same kernel size (3 × 3) is applied over all convolutional layers with a stride of 1 pixel. Each max-pooling layer has 2 × 2 regions. The VGG model has two fully connected hidden layers and one fully connected output layer [23]. The Rectified Linear Unit (ReLU) activation function is assigned consecutively to each convolutional layer. The last convolutional layer is followed by fully connected (FC) hidden layers.

### *2.5. Support vector machine*

A support vector machine (SVM) is a learning technique that is initially designed to fit a linear boundary between two binary problem samples, ensuring maximum robustness in terms of isotropic uncertainty tolerance. Various types of functions, such as linear, polynomial, and radial basis function (RBFs), are widely applied to transform the input space into the desired function [24,25]. In this study, we used a linear SVM; the training set of features was applied as the input to train a conventional linear SVM, and the testing set of features was applied to obtain image labels for frame test prediction. The scikit-learn machine learning library was chosen for implementing the linear SVM. We examined the SVM method with the different parameters of gamma ('0.1', 'auto'), C = 1, and kernel ('linear', 'rbf'), and we found the best accuracy for gamma = 0.1, C = 1, and kernel = linear.

### *2.6. K-nearest-neighbors*

The k-nearest-neighbors (KNN) method is one of the most important data mining techniques that attempts to classify an unknown sample based on the known classification of its neighbors [26]. The KNN algorithm simply stores the image dataset during the training process, and when it obtains a new image, it classifies this image into a category that is very similar to the new image. In this study, classification using the KNN method was carried out with a 5-times-trial using different k values for each experiment. We partitioned the data into 10 folds and utilized 10-1 folds for training and the remainder (1-fold) for validation. The k values of 1, 3, 5, 7, and 9 were applied to obtain the best performance for peaberries and normal coffee bean images [27].

### *2.7. Classification accuracy*

The classification accuracy for the CNN, linear SVM and KNN methods refers to the ratio of items that are positive and classified as positive and to those that are negative and classified as negative, as described in equation (1).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

where *TP*, *TN*, *FP*, and *FN* are the number of true positives, true negatives, false positives, and false negatives, respectively.

### *2.8. Raspberry Pi and Camera Module*

This research demonstrates a real-time application for coffee bean image classification by using a Raspberry Pi [28]. The Raspberry Pi Foundation developed a series of credit-card-sized single, electronic board, compute modules named Raspberry Pi to promote the teaching of basic computer science in institutes and developed countries [29]. In this study, we chose the Raspberry Pi 3 Model

B. The Raspberry Pi 3 has 1 GB of RAM, a 64-bit ARM quad-core processor, 4 USB ports, a wired LAN port, and one HDMI port and supports Wi-Fi and Bluetooth wireless connections. Various additional modules, such as a camera, display, a micro SD port for loading the operating system and storing data, and different sensors, can be directly connected to the base. Raspberry Pi 3 also has a GPU and can be controlled by a simple LCD. In addition, the model also has an input/output terminal (GPIO) with 40 general-purpose pins. The GPIO allows us to use electronic devices and handle various sensors.

The original Raspberry Pi 3 Camera Module V2 was used for the camera module and was connected to the CSI-2 connector. The Camera Module V2 has an 8-megapixel SONY IMX219 sensor and can be used to capture high-definition video and still photography. Here, the libraries bundled with the camera can be used. The system supports 1080p30, 720p60, and VGA90 video modes and still captures [30]. The camera module was attached via a 15 cm ribbon cable to the CSI port on the Raspberry Pi 3. In this research, the original camera module was used instead of USB third-party cameras. The CSI-2 connector is faster than USB 2.0 [9].

The Raspberry Pi is suitable for our project because the module can be available worldwide at a very cheap price. The Raspberry Pi 3 Model B is the third generation Raspberry Pi. The total cost of the Raspberry Pi 3 system was estimated at $50.

## 3. Results and discussion

In this experiment, the front-side and back-side coffee bean images for both normal and peaberry were taken separately. We used both front-side and back-side images of a bean in the training set, validation set, and test set by mixing the order of them. For instance, the front-side of beans were used in the training set, as well as the back-side of the same beans, which were also used in the training set. It means that the system classifies classes are only ‘normal beans’ and ‘peaberries’ regardless of front-side or back-side, assuming the practical use. This experiment was a preliminary experiment for the whole system we will develop. On the whole system, a large quantity of arranged/not-arranged beans flows on a board, like a conveyor belt, regardless of the front-side or back-side. The system must classify the ‘normal’ and ‘peaberry’ regardless of the sides. In this work, we evaluated the performance and examined the limitations of three major machine learning algorithms, e.g., convolutional neural networks (CNN), support vector machines (SVM), and k-nearest-neighbors (KNN), for four different image sizes, e.g., 32×32, 64×64, 128×128, and 256×256 pixels. We also examined the differences between color image datasets and grayscale image datasets. First, we trained each model with all the above mentioned parameter combinations and evaluated the classification accuracies on the desktop PC (Section 3.2). Second, we examined the calculation time and limitations of Raspberry Pi 3 using the same datasets and models that were trained on desktop PC (Section 3.3). If we use the same datasets and pretrained models for classification, we just obtain the same results regardless of the calculation platforms. The differences between the desktop PC and Raspberry Pi 3 are the calculation time and limitations depending on CPU power, memory size, and etc. Before the comparison among the CNN, linear SVM, and KNN, we experimented with different k values (k = {1, 3, 5, 7, 9}) of the KNN method to obtain a better k value (Section 3.1).

### 3.1. Selection of k value for KNN method

The purpose of this part of the experiment is to ensure the classification efficiency of the KNN classification method and to improve the accuracy of the classification method. The results of the classification accuracy for different k values and image sizes are summarized in Table 3 and Figure 5. For both the color image case and grayscale image case and for any k value cases, we obtained the best classification accuracy with the smallest image size of 32×32 pixels, and the accuracy decreased as the image size increased. Generally, a larger image size has more information to be used in the classification. On the other hand, it is known that the KNN method tends to fail classifications as the image size increases because the method uses the Euclidean distance to estimate the nearness and the 'curse of dimensionality' problem arises at larger image sizes [31]. Regarding the k value, we obtained the best accuracy with k = 5 in most cases, so we use k = 5 hereafter in the KNN method.

**Table 3.** Results of average accuracy (mean) and standard deviation (SD) for different k values on the desktop PC.

| *(a) Color image* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 32 × 32 | | 64 × 64 | | 128 × 128 | | 256 × 256 | |
| Value of k | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| k = 1 | 95.80 | 0.015572 | 95.08 | 0.012438 | 94.29 | 0.013430 | 93.30 | 0.016019 |
| k = 3 | 96.40 | 0.011674 | 95.95 | 0.007524 | 94.86 | 0.011187 | 93.63 | 0.014423 |
| k = 5 | 96.43 | 0.012215 | 95.80 | 0.013430 | 95.08 | 0.014725 | 93.84 | 0.018525 |
| k = 7 | 95.89 | 0.014089 | 95.74 | 0.012079 | 95.11 | 0.015118 | 94.05 | 0.014834 |
| k = 9 | 95.86 | 0.017326 | 95.41 | 0.012901 | 95.02 | 0.013957 | 93.90 | 0.017167 |
| *(b) Grayscale image* | | | | | | | | |
| k = 1 | 95.14 | 0.013564 | 94.53 | 0.013564 | 93.90 | 0.015678 | 92.98 | 0.027361 |
| k = 3 | 95.59 | 0.011061 | 94.92 | 0.009544 | 94.20 | 0.010503 | 93.57 | 0.021123 |
| k = 5 | 95.62 | 0.015325 | 95.14 | 0.013710 | 94.26 | 0.017014 | 93.73 | 0.025807 |
| k = 7 | 95.32 | 0.016582 | 94.89 | 0.013430 | 94.41 | 0.016702 | 93.88 | 0.023100 |
| k = 9 | 95.23 | 0.021303 | 94.74 | 0.014385 | 94.26 | 0.017364 | 93.74 | 0.024791 |

### 3.2. Performance of the classification on desktop PC

We compared the performance of the three machine learning methods for four different image sizes in terms of the classification accuracy on the desktop PC ((Table 4 (a), (b)) and Figure 6). As a result, the classification accuracy of the proposed CNN method was better than that of the linear SVM and KNN in all image size cases and both the color image case and grayscale image case. In the CNN case, the classification accuracy has gradually improved with an increase in image size, and the best result is obtained with an image size of 256 × 256 pixels for both color images and grayscale images. In the color image case, the proposed CNN model achieved a classification accuracy of 99.70%, whereas the VGG-16, linear SVM and KNN achieved classification accuracies of 99.38%, 96.10% and 93.84%, respectively, with an image size of 256 × 256 pixels. In the grayscale image case, the CNN model reached classification accuracy of 98.49% while the VGG-16, linear SVM and KNN reached classification accuracies of 98.18%, 94.29% and 93.73%, respectively, with an image size of 256 × 256 pixels. The VGG-16 (16 layers) network required more time to train its parameters than the proposed CNN (4 layers) model. The processing time is greatly affected by the image size, yet the performances of classification accuracy were not so affected ((Table 5 (a), (b)), and (Table 6 (a), (b))). In almost all cases, the classification accuracy of the color image was better than that of the grayscale image for all three machine learning methods.

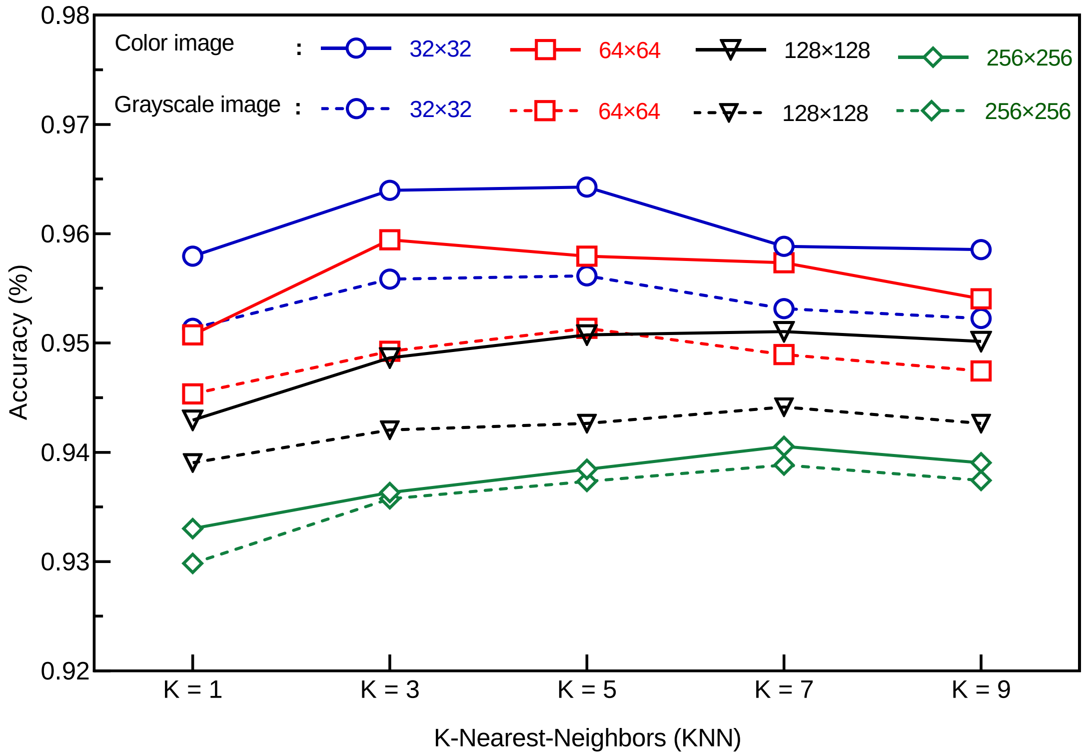



**Figure 5.** Figure shows the comparison of different k accuracies on the desktop PC for both color images and grayscale images. The solid lines represent color coffee bean images and dashed lines represent grayscale coffee bean images.

**Table 4.** Comparison of classification accuracy with different methods on the desktop PC.

| Image Size | Convolutional Neural Networks (CNN) | VGG-16 | Linear SVM | K-Nearest-Neighbors (KNN) (k = 5) |
|---|---|---|---|---|
| *(a) Color image* | | | | |
| 32 × 32 | 97.89 | 96.99 | 97.00 | 96.43 |
| 64 × 64 | 98.19 | 97.01 | 97.00 | 95.80 |
| 128 × 128 | 99.40 | 98.67 | 96.40 | 95.08 |
| 256 × 256 | 99.70 | 99.38 | 96.10 | 93.84 |
| *(b) Grayscale image* | | | | |
| 32 × 32 | 95.78 | 95.63 | 93.09 | 95.62 |
| 64 × 64 | 96.08 | 95.78 | 93.39 | 95.14 |
| 128 × 128 | 97.07 | 96.25 | 93.99 | 94.26 |
| 256 × 256 | 98.49 | 98.18 | 94.29 | 93.73 |

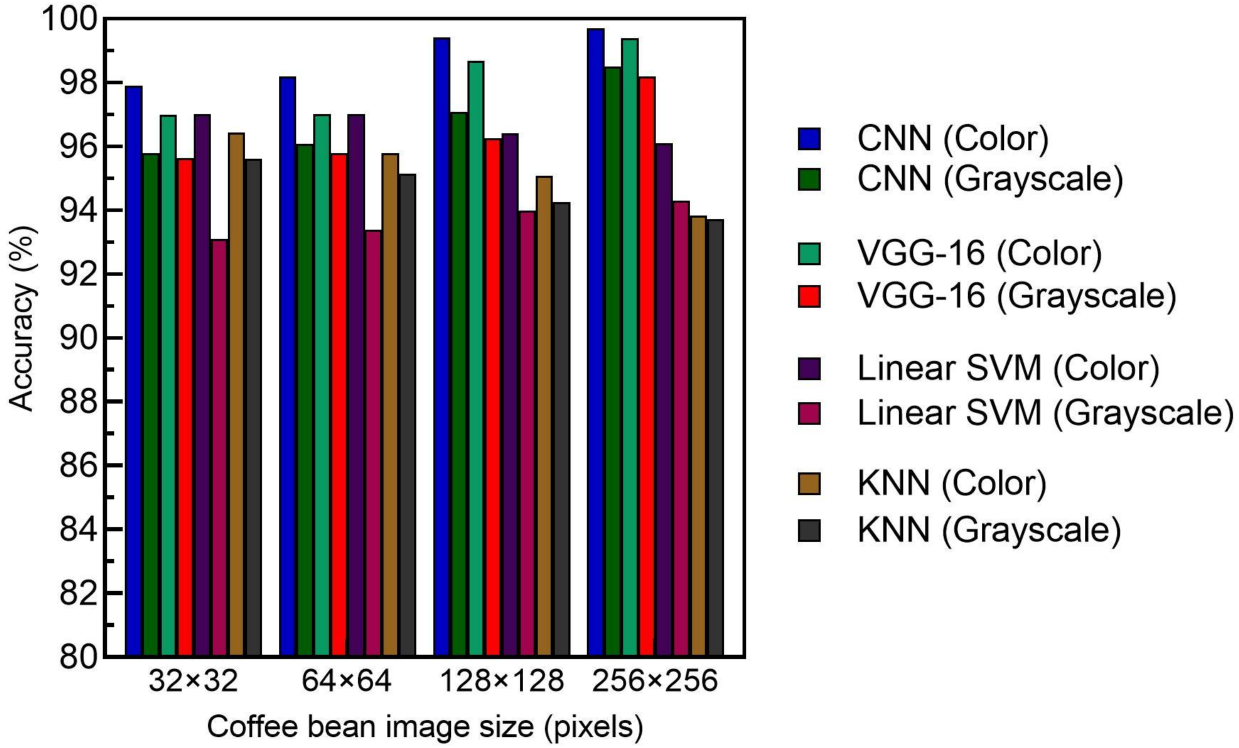



**Figure 6.** An image size wise accuracy comparison among the CNN, VGG-16, linear SVM, and KNN in both color images and grayscale images. The CNN outperformed the machine learning methods in coffee bean classification.

*3.3. Performance of the classification on Raspberry Pi 3*

Assuming that our system is employed in the least developed countries, we also examined the performance of the three machine learning techniques on Raspberry Pi 3 with all the same parameter sets that were examined on the desktop PC. Because we utilized the same models that had been trained on the desktop PC in advance, the differences between the desktop PC and Raspberry Pi 3 were limitations and calculation times. In both the desktop PC and Raspberry Pi 3, the calculation time for four different image sizes increased gradually with an increase in image size (Tables 5 and 6). Although the CNN classification method performed better than the KNN and linear SVM in terms of accuracy, the CNN consumed more calculation time than the linear SVM for all the parameter sets.

Raspberry Pi 3 could not finish the computation with the linear SVM and KNN due to hardware limitations in the case of (i) color image sizes, e.g., 128 × 128 and 256 × 256 pixels, and (ii) grayscale image sizes of 256 × 256 pixels (described as 'Memory Error' in Table 6). In both the color image case and grayscale image case, the calculation time of the CNN was much higher than that of the linear SVM for four different image sizes (Table 6).

**Table 5.** Comparison of calculation time (seconds) with different methods on the desktop PC.

| Image Size | Convolutional Neural Networks (CNN) Prediction Phase | VGG-16 Prediction Phase | Linear SVM Prediction Phase | K-Nearest-Neighbors (KNN) (k = 5) Prediction Phase |
|---|---|---|---|---|
| *(a) Color image, desktop PC* | | | | |
| 32 × 32 | 0.004347 | 0.015784 | 0.000084 | 0.000084 |
| 64 × 64 | 0.005229 | 0.016046 | 0.000102 | 0.000085 |
| 128 × 128 | 0.006191 | 0.417148 | 0.000108 | 0.000090 |
| 256 × 256 | 0.014570 | 0.349104 | 0.000110 | 0.000097 |
| *(b) Grayscale image, desktop PC* | | | | |
| 32 × 32 | 0.004074 | 0.010176 | 0.000059 | 0.000075 |
| 64 × 64 | 0.004401 | 0.015944 | 0.000099 | 0.000084 |
| 128 × 128 | 0.005238 | 0.025215 | 0.000101 | 0.000085 |
| 256 × 256 | 0.010665 | 0.291822 | 0.000108 | 0.000091 |

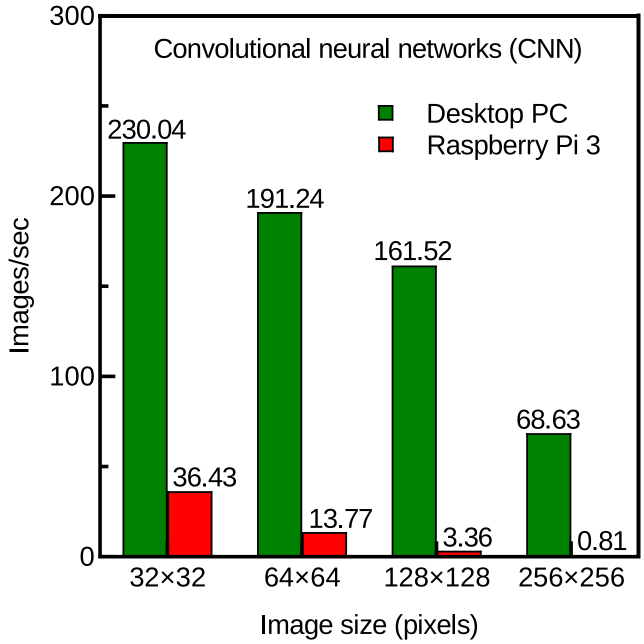
**Table 6.** Comparison of calculation time (seconds) with different methods on the Raspberry Pi 3.

| Image Size | Convolutional Neural Networks (CNN) Prediction Phase | VGG-16 Prediction Phase | Linear SVM Prediction Phase | K-Nearest-Neighbors (KNN) (k = 5) Prediction Phase |
|---|---|---|---|---|
| *(a) Color image, Raspberry Pi 3* | | | | |
| 32 × 32 | 0.027451 | 0.109403 | 0.000041 | 0.106982 |
| 64 × 64 | 0.072632 | 0.339624 | 0.000045 | 0.470734 |
| 128 × 128 | 0.297931 | 1.421610 | Memory Error | Memory Error |
| 256 × 256 | 1.232757 | 2.947290 | Memory Error | Memory Error |
| *(b) Grayscale image, Raspberry Pi 3* | | | | |
| 32 × 32 | 0.026891 | 0.105652 | 0.000041 | 0.033003 |
| 64 × 64 | 0.071804 | 0.215478 | 0.000044 | 0.158468 |
| 128 × 128 | 0.287301 | 1.322205 | 0.000047 | 0.721037 |
| 256 × 256 | 1.176398 | 1.584646 | Memory Error | Memory Error |

The prediction speed of color images was much higher than that of grayscale images for both desktop PC and Raspberry Pi 3. In the case of desktop PC, the KNN method's prediction speed was lower than linear SVM and CNN for four different sizes of color and grayscale images. On the other hand, in the case of the Raspberry Pi 3, the linear SVM classification method's prediction speed was lower than CNN and KNN for four different sizes of color and grayscale images (Tables 5 and 6).

To estimate the feasibility of these machine learning techniques on the Raspberry Pi 3 for practical use, we summarized the number of images processed per second in Figure 7. As a result, the trained CNN could classify approximately 13.77 coffee bean images per second with an accuracy of 98.19% for the classification with a color image size of 64 × 64 pixels on Raspberry Pi 3. This combination of a number of images per second and classification accuracy can motivate companies and poor farmers to check our system for a low price on the classification of peaberries and normal coffee beans for the least developed countries.

(a) Color image




(b) Grayscale image

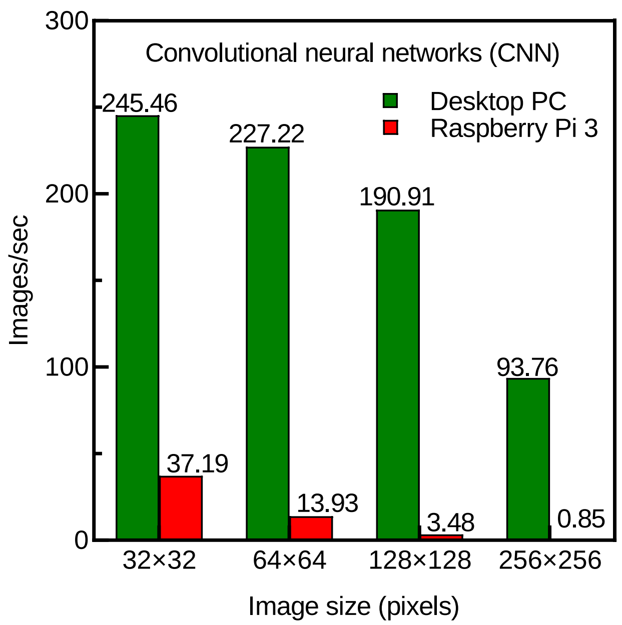



**Figure 7.** Image size wise (a) color coffee bean image and (b) grayscale coffee bean image processed per second by the CNN. The number of processed images of small size is much greater than that of large-sized images, and the desktop PC's total number of images processed per second is much greater than that of Raspberry Pi 3.

The important points of this work are as follows. First, the classification between the peaberry and normal bean is a challenging task compared to other general sorting tasks of fruits and vegetables. This is because the peaberry's color and shape are similar to the normal bean, and the sorting is difficult even for manual inspection by a human. This is why we tried to use not simple traditional image processing methods but machine learning techniques. Second, we assume that we will use our system in the least developed countries, and we examined the availability and limitation of the Raspberry Pi system on the classification in terms of accuracy and calculation time. For instance, 30 kg or 60 kg of gunny sacks are usually used for the green coffee trade. There are about 300,000 beans in a 60 kg sack. In this study, we examined the processing speed for one bean classification and found that the Raspberry Pi 3 could classify one bean by 0.03 seconds. This means that the system has a potential to sort approximately 26 kg of coffee beans per hour, which was six times faster than the hand-picking and five times faster than the reported sorting system [32].

## 4. Conclusions

The purpose of our study was to estimate the Raspberry Pi 3 system's availability for the sorting of peaberries and normal beans in the least developed countries. There are two strong demands for the sorting of peaberries from normal beans. The first demand is for uniformity of the beans in the roasting process because the nonuniformity leads to a poor coffee taste. The second demand is the special value of peaberries on the market. However, the shape and color of peaberries are very similar to those of normal beans, and sorting them is a difficult task, even for well-trained specialists on hand picking and for ordinary automatic sorting machines. In this study, image processing and machine learning techniques were adapted for sorting peaberries and normal coffee beans. For machine learning techniques, we compared the performances of the CNN, linear SVM, and KNN from the viewpoints of classification accuracy and calculation time on the Raspberry Pi 3 system.

To improve the performance, we modified the CNN architecture from our previous studies [14]. Our analysis shows that CNN accuracy is the best for both color coffee bean images and grayscale coffee bean images with any image size compared to the VGG-16, linear SVM and KNN methods. On the other hand, we observed that Raspberry Pi 3 could not finish computation with the linear SVM and KNN due to hardware limitations in the case of large-sized images. Although the CNN classification accuracy was increased when the image sizes were increased, the calculation time was not fast enough for practical use when we utilized images larger than 128 × 128 pixels on Raspberry Pi 3.

As a result, we conclude that color images with a size of 64 × 64 pixels and CNN with the proposed structure are the best combination for the Raspberry Pi 3. Under these conditions, the number of images per second (13.77 images) and classification accuracy (98.19%) are satisfactory for practical use as a low-price classification system of peaberries and normal coffee beans for the least developed countries.

## Conflicts of Interest

The authors declare no competing interests.

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**Biography**

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