# Recognition of Roasted Coffee Bean Levels using Image Processing and Neural Network

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# Recognition of Roasted Coffee Bean Levels using Image Processing and Neural Network

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**Abstract**. The coffee beans roast levels have some characteristics. However, some people cannot recognize the coffee beans roast level. In this research, we propose to design a method to recognize the coffee beans roast level of images digital by processing the image and classifying with backpropagation neural network. The steps consist of how to collect the images data with image acquisition, pre-processing, feature extraction using Gray Level Co-occurrence Matrix (GLCM) method and finally normalization of data extraction using decimal scaling features. The values of decimal scaling features become an input of classifying in backpropagation neural network. We use the method of backpropagation to recognize the coffee beans roast levels. The results showed that the proposed method is able to identify the coffee roasts beans level with an accuracy of 97.5%.

## 1. Introduction

Coffee is one of the most widely consumed beverages in the world [1]. In the coffee processing, there is a roasting step that will produce variety of coffee bean roasts levels. There are three levels of roasting, light roast, medium roast, and dark roast. Furthermore, there are more specific coffee bean roasts levels, such as French roast, Vienna roast, Cinnamon roast, etc. [2]. Usually those terms of roasting coffee are used by master roasters/professionally coffee roasters. In this researched, we propose to design a method to identify the specific coffee bean roasts levels.

Recently, there are some researches on explore any of coffee processing, such as the plant processing, the roasting processing, and grinding processing, etc. The aim is how to get specialty coffee by its processing such as the variety of taste, aroma, and acidity. This is because from the beginning until the green beans with the result of roasting coffee has the characteristic aroma [3]. The researched about green beans has been shown how to create a computer vision system for coffee beans classification based on computational intelligence techniques [4]. In the roasting processing, there is a research that monitors the roasting process by using near infrared spectroscopy to be able to predict the two parameters that are most relevant copies when roasting processing [5]. In addition, there is also a research that monitors the roasting processing based on digital images using neuro-fuzzy models [6].

Neural networks are algorithms developed to mimic the human logic and the thinking process. The application of many types of networks, including the backpropagation network, has been demonstrated in the past for signal and image processing. The backpropagation algorithm has a massively parallel architecture well suited for signal and image processing applications. The backpropagation (BP) network architecture consists of an input layer of nodes and an output layer of nodes. There are usually one to two hidden layers of nodes. All the nodes in each layer are connected to all the nodes in the next layer by a set of weights. The values of the weights are adjusted during the training process to obtain the desired response of the output nodes when a training set of data is applied to the input nodes [7]. The most widely applied neural network algorithm in image classification remains the feed forward backpropagation algorithm.

In this researched area, the researcher try to cover all steps in the roasting processing until find the characteristic coffee aroma. In contrast to some of the above research, we propose a method of recognition of coffee roasts levels based on digital images using image processing and backpropagation neural network. This method aims to recognize the results of coffee bean roasts level from a digital image to determine the degree of roasting. It is intended that the amateurs also can distinguish the levels of roasting.

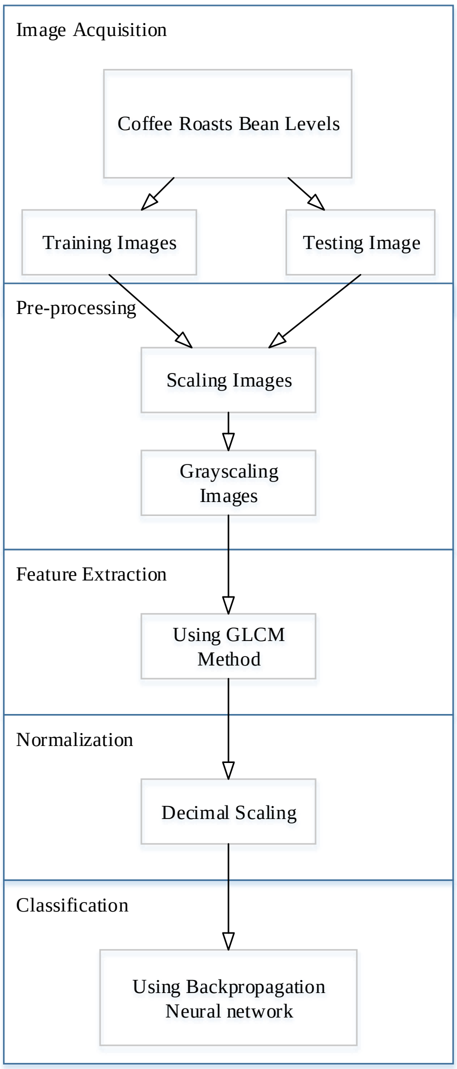


**Figure 1**. Research Methodology

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## 2. Materials and Methods

The general architecture of the research methodology consisted of five steps. The first step was the image acquisition using a camera phone in which image acquisition results will be used as training images and test images. The second step was the pre-processing of images consisted of scaling and gray scaling. The third step was the extraction of each image features of with a value of 16 Haralick features of GLCM method. The fourth step was the normalization of the extracted features using decimal scaling. The final step was image classifications using artificial neural network backpropagation. The classified system was implemented by web based application using Java programming and MySQL database. The flow of general architecture of the research methodology can be seen in Figure 1.

### *2.1. Database of Coffee*

cc Roasting was part of the coffee processing. The result of coffee beans roasted had four levels in general, i.e., light coffee, medium coffee, dark coffee, and extra dark coffee. Then, each level of coffee roasts beans had colors gradation so there were more variety of coffee roast bean levels such as gradation colors of light level, i.e., Green Coffee, Begins To Pale, Early Yellow, Yellow-Tan. The gradation colors of medium level, i.e., Light Brown, Brown, 1st Crack Start, and 1st Crack Done. The gradation colors of dark level, i.e., City Roast, City+, Full City, and Full City+ 2nd Crack. The gradation colors of extra dark levels, i.e., Vienna Light, Full French, Charcoal Dead, and Fire Risk. The images can be seen in Figure 2.


**Figure 2.** Dataset of Coffee

The images data that had been taken by smartphone for 10 times and 10 positions of each coffee bean roasts level 80% training data and 20% test data for each image data.

### *2.2. Pre-Processing*

The pre-processing step would do optimization in research result to produce a better image before feature extraction phase. The image pre-processing consists of two parts. The first step was to reduce the image dimension (scaling) and then the second step was to turn it into a grey image (gray scaling).

The original image dimension is 3120 x 4160 pixels. Image acquisition results had a size large enough so that the necessary process of reducing the size of the image. The entire image acquisition results would be reduced in size to 490 x 316 pixels.

After scaling processing, the image would be processed from RGB form into the shape of gray level image. This phase was done so that the image could be processed to next step - feature extraction.

### 2.3. Feature extraction

The extraction of image features method was Gray Level Co-Occurrence Matrix (GLCM). GLCM is one of the second-order texture analysis methods [8]. GLCM represents the relationship of two neighboring pixels in which two pixels associated has a certain intensity of gray and a certain distance and direction between them [9].

Parameter on GLCM was the direction and the distance between neighboring reference pixel by pixel and gray level in the image. Each pixel could have neighboring pixels of the eight directions, i.e. 0°, 45°, 90°, 135°, 180°, 225°, 270°, or 315°. However, the selection of the angle was 0° will produce the same value GLCM valuable to the angle of 180°. The concept also applied to an angle of 45°, 90°, and 135° [8]. Therefore, the angles used were 0°, 45°, 90°, and 135°. Eight directions adjacent GLCM can be seen in Figure 3.

The next parameter in GLCM was distance. Distances on GLCM represented the number of pixels that were between the reference pixels and the neighboring pixels. Then, the steps by step of GLCM were to make framework matrix. First, The size of framework matrix based on the intensity of image gray level. The Second, making co-occurrence matrix. Co-occurrence means fill the framework matrix. The third, making symmetric matrix by adding co-occurrence matrix with transpose matrix. The last step was matrix normalization by losing dependency of image size by dividing every matrix element so the total of all element are 1. The counting of statistic feature could be done by co-occurrence matrix being normalize. The statistic feature consists of counting the energy, entropy, contrast, inverse difference moment, and correlation. This feature extraction had 160 feature extractions, which were got from using 16 statistic features with 4 directions (0°, 45°, 90°, and 135°).

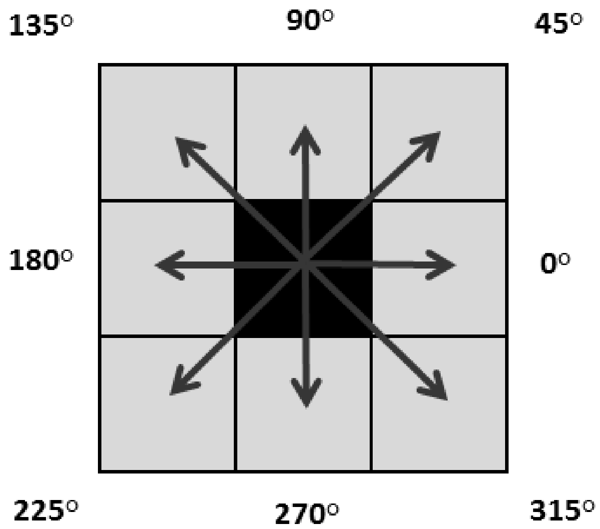


**Figure 2.** Co-occurrence matrix directions for extracting texture features

### 2.4. Data normalization

Normalization is a technique of pre-processing of data such as to transform the value attribute of a dataset so it is in a certain range, for example between 0 and 1. The normalization can be used in problems such as data classification and clustering neural network [10].

The result of feature extractions were normalized before doing the next step - classification that used backpropagation method. Normalization technique which used was decimal scaling. Normalization would scale the decimal data normalizations by moving the decimal point which was determined by the maximum absolute value of an attribute.

*2.5. Classification use backpropagation neural network*

Backpropagation method was an artificial neural networks training which are supervised learning. Backpropagation required the target as a reference in the training process, the purpose of propagation was to set the value of the errors in the network become minimums, or it means to create an output value closed to the target [11]. The result of the backpropagation training was the form of the final grade. The final value was a representation of learning process.

Backpropagation method consists of two phases, that is a forward phase and backward phase [12]. Methods of propagation make changes to the value of the weights in the backward phase by using the error output. Forward phase must be first in order to obtain the error value. In this researched backpropagation was used to perform image classification of 16 levels of coffee bean roasted.

## 3. Result and discussion

Tests conducted to determine the ability of a propagation method in identifying 16 levels of coffee roasts beans. The ability of the system to identify the level of roast depends on backpropagation training process for generating weight training process that will be used in the testing phase. Backpropagation parameters used in the training phase can be seen in Table 1.

**Table 1**. Backpropagation parameters

| No. | Parameters | Information |
|---|---|---|
| 1 | Input Neuron | 160 (from feature extraction) |
| 2. | Hidden Neuron | 30 |
| 3 | Output Neuron | 16 (coffee bean roasts levels) |
| 4. | Function Activation | Sigmoid |
| 5. | Maximum Epoch | 500 |
| 6. | Minimum Error | 0.01 |
| 7. | Learning Rate | 0.9 |
| 8 | Epoch | 1000 |

By using the parameters in Table 1, the data testing used 10 images training for every coffee bean roasts level. This means that used 160 for all image training. To calculate the accuracy of these tests is used Equation (1).

$$Accuracy = \frac{Number\ of\ correct\ data}{\text{The amount of overall data}} x100\% \tag{1}$$

The accuracy of the data testing result can be seen in Table 2. Table 2 shows the actual amount of output corresponding to the desired output at every roast coffee beans level with the value of accuracy obtained by using Equation (2)[10].

$$z_j = f(z\_net_j) = \frac{1}{1+e^{-z\_net_j}} \tag{2}$$

**Table 2**. Accuracy

| No. | level of roast coffee | Actual number of outputs in accordance with the Desired Output | Overall Accuracy |
|---|---|---|---|
| 1. | Green Coffee | 10 | 100% |
| 2. | Begins To Pale | 10 | 100% |
| 3. | Early Yellow | 10 | 100% |
| 4. | Yellow-Tan | 10 | 100% |
| 5. | Light Brown | 10 | 100% |
| 6. | Brown | 10 | 100% |

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Table 2. Cont.

| | | | |
|---|---|---|---|
| 7. | 1st Crack Start | 10 | 100% |
| 8. | 1st Crack Done | 10 | 100% |
| 9. | City Roast | 10 | 100% |
| 10. | City+ | 10 | 100% |
| 11. | Full City | 9 | 90% |
| 12. | Full City+ 2nd Crack | 10 | 100% |
| 13. | Vienna Light French | 10 | 100% |
| 14. | Full French | 10 | 100% |
| 15. | Charcoal Dead | 8 | 80% |
| 16. | Fire Risk | 9 | 90% |

Based on the results in table 2, the overall accuracy can be calculated. Overall accuracy was obtained by using equation (1) by adding the appropriate amount of actual output to the desired output of the overall accuracy divided by the total number of coffee beans roast levels.

$$Accuracy = \frac{156}{160} x100\% = 97{,}5\%$$

The next phase was the testing of the maximum parameter selection epoch in the training process. Selection of maximum parameter epoch performed 16 times using the parameters in Table 1 with a maximum parameter different epoch. This research was performed using the same initial value. The result of testing process of 10 images per coffee beans roast level can be seen in Table 3 and the graph in Figure 4.

**Table 3.** Testing the maximum value of epoch

| No. | Max | Actual number of outputs in accordance with the Desired Output | | | | | | | | | | | | | | | | Overall |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Epoch | CG | BP | EY | YT | LB | B | CS | CD | CR | C | F | FC | VLC | FF | CD | FS | Accuracy |
| 1. | 100 | 7 | 8 | 8 | 6 | 9 | 8 | 8 | 10 | 7 | 6 | 8 | 8 | 7 | 7 | 10 | 8 | 56% |
| 2. | 200 | 10 | 9 | 6 | 5 | 9 | 7 | 9 | 6 | 7 | 9 | 7 | 7 | 7 | 7 | 10 | 7 | 60% |
| 3. | 300 | 7 | 7 | 8 | 7 | 10 | 8 | 7 | 8 | 2 | 10 | 7 | 6 | 8 | 6 | 10 | 10 | 64% |
| 4. | 400 | 8 | 6 | 8 | 8 | 7 | 8 | 6 | 9 | 8 | 7 | 8 | 5 | 9 | 8 | 8 | 8 | 72% |
| 5. | 500 | 7 | 8 | 7 | 9 | 8 | 9 | 8 | 7 | 9 | 9 | 9 | 7 | 9 | 6 | 9 | 8 | 74% |
| 6. | 600 | 9 | 9 | 9 | 9 | 10 | 9 | 9 | 8 | 9 | 8 | 9 | 6 | 9 | 8 | 8 | 8 | 74% |
| 7. | 700 | 7 | 9 | 9 | 9 | 6 | 8 | 9 | 9 | 9 | 9 | 9 | 8 | 7 | 8 | 9 | 9 | 78% |
| 8. | 800 | 10 | 9 | 10 | 9 | 10 | 10 | 9 | 10 | 9 | 10 | 10 | 8 | 10 | 9 | 10 | 8 | 78% |
| 9. | 900 | 10 | 10 | 10 | 10 | 8 | 10 | 10 | 10 | 10 | 9 | 10 | 10 | 10 | 10 | 9 | 9 | 90% |
| 10. | 100 | 10 | 10 | 10 | 10 | 10 | 10 | 8 | 10 | 10 | 10 | 10 | 9 | 10 | 10 | 8 | 9 | 94% |

In Table 3, it can be seen for every level coffee roasts beans, Green Coffee is represented by GC, Begins To Pale represented by BP, Early Yellow represented by EY, Yellow-Tan was represented by YT, Light Brown represented by LB, Brown represented by B, 1st Crack Start is represented by CS, 1st Crack Done represented by CD, City Roast represented by CR, City+ is represented by C, Full City represented by F, Full City+ 2nd Crack represented by FC, Vienna Light French represented by VLC, Full French represented with FF, charcoal Dead represented by CD, and Fire Risk is represented by FS.

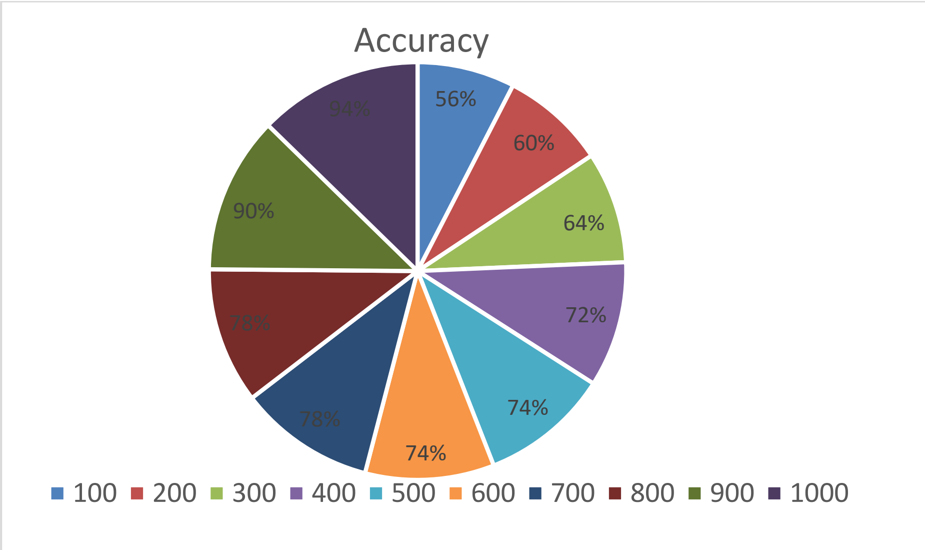


**Figure 3**. Testing the maximum value of epoch

Table 3 shows the maximum epoch, the number of actual output in according to the desired level of output per coffee beans roasted as well as accuracy. The test results are shown in Table 3 and Figure 4 shows that the epoch to a maximum of 1000, reached 97.5% accuracy. It shows when the more epoch increases, the accuracy done.

## 4. Conclusion

Based on the data testing result performed, the recognition of coffee beans roasts level can be classified by using backpropagation neural network methods. The coffee profiles according to the predetermined targets with accuracy value reached 97.5% with the maximum value epoch 1000. The larger the value, the accuracy will increase too. The subsequent researched is expected to recognize by combining other methods to improve.

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