Quality Classification of Copra Using Convolutional Neural Network

Crizzan Bel Colubio
Department of Electronics Engineering
University of Southeastern Philippines
Davao City, Philippines
crizzanbelcolubio@gmail.com

Von Patrick Denorte
Department of Electronics Engineering
University of Southeastern Philippines
Davao City, Philippines
vpdenorte@gmail.com

Rica Panga
Department of Electronics Engineering
University of Southeastern Philippines
Davao City, Philippines
ricapanga@gmail.com

***Abstract*—This study introduces a system in quality classification of copra in compliance to the Philippine National Standard (PNS) for Copra. A model was developed using Convolutional Neural Network that classifies copra based on a set of pre-classified images. The process is divided into three steps: image acquisition, pre-processing, and network training. A total of 1350 images were used for the network. 80% of the data were allotted for the training set, and the remaining 20%, for the validation set. The result showed 90.74% accuracy in classifying the Grade I, Grade II, and Grade III copra.**

***Keywords*—copra, image processing, image segmentation, deep learning, convolutional neural network**

I. Introduction

The Philippines is the second largest producer of coconuts in the world after Indonesia, with 1.489 million MT of exports in 2015 [1]. One of the products of coconut is copra: the dried kernel of a coconut which produces coconut oil, and copra meal as a by-product. Copra production in the Philippines is standardized under the Philippine National Standard (PNS) for Coconut (Copra). This standard is used for the classification, tolerances, and methods of sampling and analyses of copra [2].

Although the procedure of the classification for copra is already laid out by the PNS, producers and traders of copra usually classify goods based only on physical attributes such as color, hardness, and smell. This results in an inconsistent classification of copra among different producers and traders. In order to attain a consistent conjecture of the classification of copra, a model can be constructed using Convolutional Neural Network (CNN) that will classify copra based on a centralized set of pre-classified images.

With a model that classifies copra, producers and traders can classify their goods around a distinct reference for uniformity. The model can also be incorporated in production lines such as in the coconut oil production to filter out copra that do not meet the minimum requirements. This study can also provide future researchers information on the construction of models using CNN particularly the methods used in image segmentation and clustering.

This study is limited to the data extracted by standard imaging devices that is the RGB color space for use of the classification of copra, in this case only the following parameters can be determined based on the PNS for copra: color of meat, extraneous matter, and aflatoxin-related molds (ARM). Furthermore, the model is designed to classify copra by individual pieces with a solid background. It is also worth mentioning that this study only proposes a neural network model that classifies copra and does not present a system for use in copra-related productions.

II. Review of Related Literature

A. Copra

Copra is produced by drying mature coconut kernels either by smoke drying, sun drying, or kiln drying. It is dried from an initial moisture content of 70% to the required 7% moisture content in order to produce coconut oil [3]. Preferably, it should be free from extraneous matter, molds, smoke, and other contaminants.

1) Characteristics: Copra can be characterized by the color of its meat, extraneous matter found on its surface, and molds present. The color can range between a white color to a dark brown color, depending on the method of drying used. Extraneous matter is any unwanted material including dirt, dust, soil, insects or any other material or substance present, adhered or incorporated to the copra. Copra can also inhibit aflatoxin-related molds (ARM) during the drying process. Aflatoxin is a group of toxic compounds generally produced by strains of the fungi, Aspergillus flavus and Aspergillus parasiticus on suitable hosts or substrates such as copra, corn, peanut and other oilseeds which can cause severe human and animal diseases. ARM indicates a presence of yellow green mold together with penetrating mold. Penetrating mold causes indentations or holes on the surface of the copra and can be visibly seen on the cross section of a split copra [2].

2) Classification: Copra can be classified by its physical and analytical characteristics. The final classification is deduced from the weight of the sample taken from a group of copra over the total weight of the group [2].

TABLE I. Classification Based on Characteristic Quality of Copra (PNS)

Parameters	Grade 1	Grade 2	Grade 3
Color of meat	Clean, white to pale yellow	Brown to dark brown	Brown to dark brown
Extraneous	0.25	0.75	1.0

matter (% max)			
ARM (% max)	0	10	20

B. Significant Deep Learning Developments

1) AlexNet: The network the researchers designed was used for classification of 1.2 million high-resolution images with 1000 possible categories. The network was made up of five convolutional layers, max-pooling layers, dropout layers, and 3 fully connected layers. To make the training faster, non-saturating neurons and an efficient GPU implementation of the convolution operation were used. To avoid overfitting, the dropout method was employed. The data showed that the achieved top-1 and top-5 error rates are 37.5% and 17%. The variant of this model also achieved a top-5 test error rate of 15.3% [4].

2) ZF Net: Since there is no clear understanding of why Large Convolutional Network model performs well and how it might be improved, the researcher explored these issues. They introduced a novel visualization technique that gives insight into the function of intermediate feature layers and the operation of the classifier. They demonstrated that the trained model is highly sensitive to local structure in the image and is not just using broad scene context. An ablation study on the model revealed that having a minimum depth to the network, rather than any individual section, is vital to the model's performance [5].

3) VGG Net: This network passes an image through a slack of covolutional layers with only 3×3 convolution filters, incorporating three non-linear rectification layers instead of a single one, which makes the decision function more discriminative. A stack of convolutional layers is followed by three Fully-Connected layers. The training was carried out by optimising the multinomial logistic regression objective using mini-batch gradient descent with momentum. The researchers performed training and evaluation on four GPUs installed in a single system, as well as train and evaluate on full-size (uncropped) images at multiple scales [6]..

C. Related Studies

1) Characteristic Recognition of Copra Using Image Processing: When drying copra, sulfur can be added in order to prevent the accumulation of fungi and bacteria owing to its antimicrobial properties. It is a toxic ingredient that is particularly harmful to the respiratory system. The fumigated copra forms a sulfur patch that is comparable to normal copra. To prevent the inclusion of sulfur fumigated copra from being processed further to coconut oil, the researchers developed an automated system for examining the copra using image processing techniques such as segmentation and feature extraction. The results show 70% efficiency in classifying sulfur fumigated copra from normal copra [3].

2) Color Quality Assessment of Coconut Sugar Using Artificial Neural Network (ANN): The quality classification of coconut sugar is generally done by manual inspection of the standard parameters set by the PNS. To solve this problem, the researchers developed an automated method of classifying the color quality of coconut sugar using image processing techniques and pattern recognition. There were 300 images involved where 70% of these were used for training the network, 15% for validation, and 15% for testing [7].

3) Classification of Flesh Aromatic Coconuts in Daylight: The study focused on developing an efficient and accurate classification for flesh aromatic coconuts in daylight by using image processing techniques. The color of the coconut's rind around the bottom of aromatic coconuts are correlated with coconuts age. A total of 150 aromatic coconuts were sampled with 50 coconuts for each layer. It was concluded from the results that the methods used by the researcher can classify the fresh aromatic coconut in natural light with an error of 7.2% for the single layer, 20% for the one and a half layer, and 23% for the double layer [8].

III. METHODS

The images of copra are classified using digital image processing. It is done using MATLAB with Image Processing Toolbox. The process is divided into three steps: image acquisition, pre-processing, and network training.

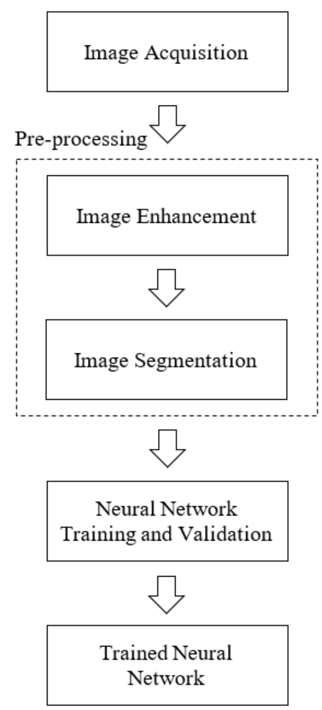

Fig. 1. Methodological framework

A. Image Acquisition

There are three classifications of copra stated by the PNS: *Grade I, Grade II, and Grade III* [2]. For each classification, 150 images of copra pieces were acquired per company which were pre-classified by copra experts, with a total of 1350 images to be used for the training and validation of the CNN.

For the image acquisition setup, the camera is mounted parallel to the surface, 0.3 meters away from the surface. Each copra piece is placed on a solid blue background.

The images are then placed on folders corresponding to their classification, e.g. the Grade I images in 'grade1' and so on. This step is done to automatically label the images based on the parent directory.

B. Image Pre-Processing

Before the images are fed to the neural network, they are first enhanced and segmented to produce a more accurate neural network.

1) Image enhancement: The acquired images are too resource-extensive for the neural network and the machine which are shot at 5MP, so the images are first cropped to 1280x1280 px and downconverted to 512x512 px. These image dimensions are enough for training the neural network while not sacrificing too much pixel information.

2) Image segmentation: The training of the neural network requires a region of interest (ROI) to be specified for accurate results. Before feeding the images for training, the colorspace of the images is converted from RGB to L*a*b* for a more accurate color representation using MATLAB's Image Processing Toolbox. Then the background is segmented from the foreground (copra) with the color thresholds in Table II for each channel. A binary mask is generated from the original image where holes are also filled, and the pixels in the original image where BW is false is set to zero (black).

TABLE II. L*A*B* COLOR THRESHOLDS

Channel	Min. threshold	Max. threshold
L*	0.197	99.663
a*	-22.840	43.387
b*	-8.398	38.325

Fig. 2. Cropped original image

Fig. 3. Generated BW mask

Fig. 4. Final masked image

C. Neural Network Training and Validation

After the images have been pre-processed, they are then fed to the CNN. The images are divided into sets for training and validation. 80% of the data, or 1080 images, is allotted for the training set, and the remaining 20%, or 270 images, for the validation set.

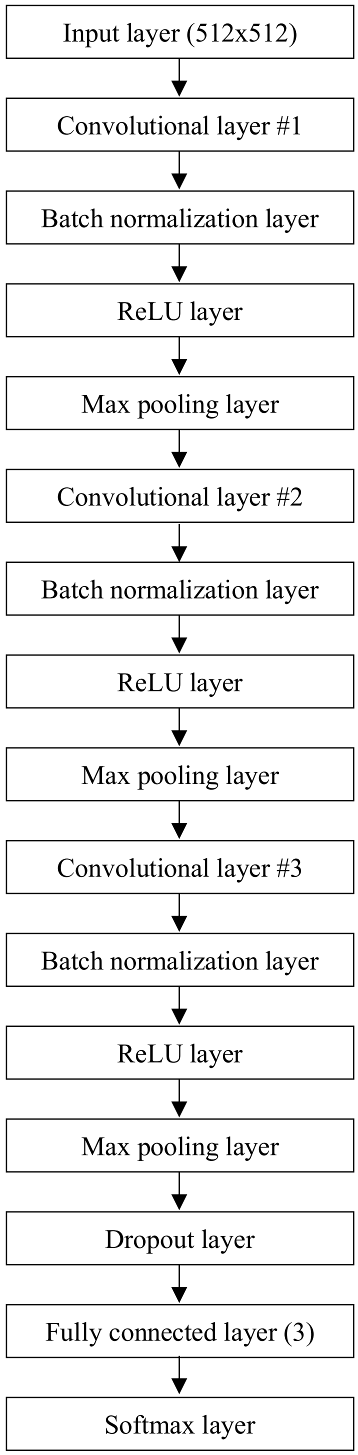

Fig. 5. Neural network architecture

The network consists of four (4) convolutional layers, three (3) max-pooling layers, a dropout layer, a fully-connected layer, and a softmax layer [9].

For the training options, the network is trained using the stochastic gradient descent with momentum (SGDM) solver with an initial learning rate of 0.01. The maximum number of epochs is set to 30 with a mini-batch size of 32 resulting in a total of 990 iterations where the data is shuffled every epoch, which is when the training data set has completed a forward and backward pass.

The network accuracy is calculated with the validation data at every 50 iterations during training to compare the progress of the accuracy of the network. At the maximum iteration, the final validation accuracy is calculated. The accuracy is the percentage of the predicted labels that matched the true labels out of all the predicted labels [10].

IV. Results

The following neural network is trained on a Nvidia GeForce GTX 950 GPU with MATLAB's Parallel Computing Toolbox. It utilizes the architecture in Fig. 5 and the parameters of the layers are described in Table III.

TABLE III. Weight Layer Parameters

Layer	**Filter size**	**No. of filters**	**Padding**	**Stride**
Conv #1	9	32	1	2
Conv #2	7	64	1	2
Conv #3	5	128	1	2
Maxpool	3	-	1	2

A smaller filter size and stride retains more pixel information from the previous layers as a larger filter size and stride might be skipping relevant information.

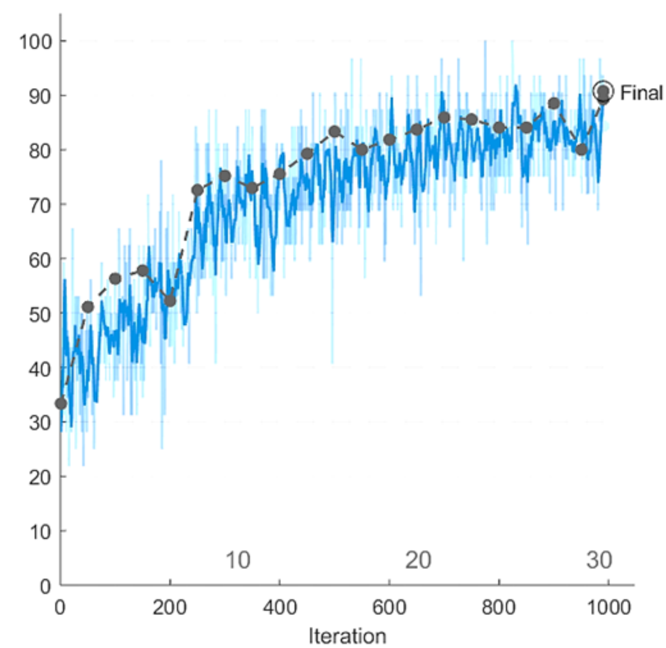

Fig. 6. Training accuracy (blue) vs. validation accuracy (dotted) graph

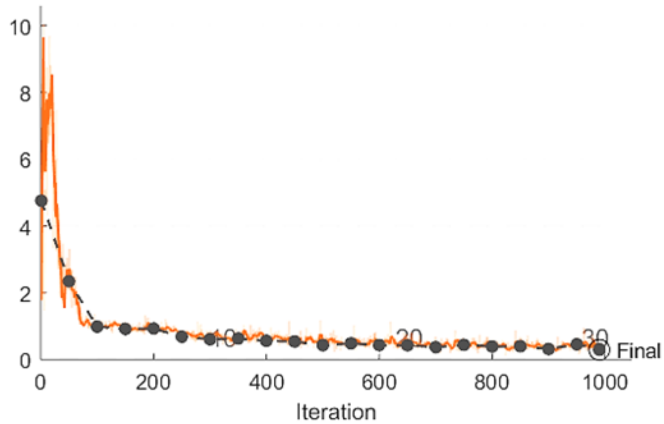

Fig. 7. Training loss (orange) vs. validation loss (dotted) graph

The final accuracy is calculated using the formula:

$$Accuracy\ (\%) = \frac{No.of\ correctly\ predicted\ val.images}{Total\ no.of\ val.images} \times 100$$

The network achieved a final accuracy of 90.74%, or 245 correctly predicted validation images out of 270 validation images.

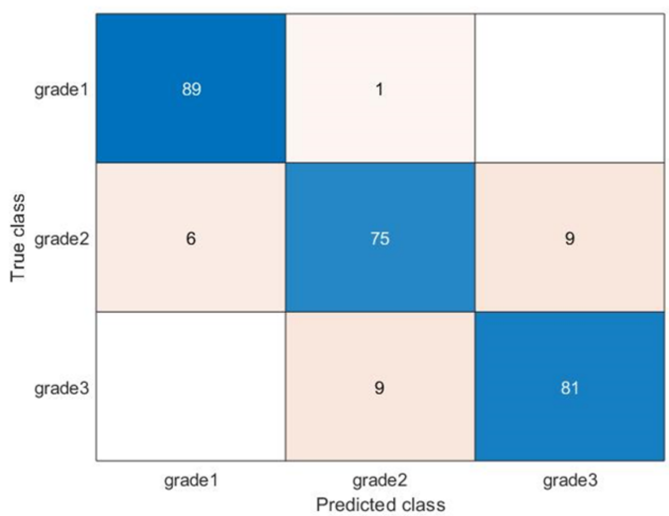

Fig. 8. Confusion matrix chart of validation dataset

V. Conclusion

With an accuracy of 90.74%, the neural network is suitable for copra classification by using only a total of 16 layers for the architecture. At 30 epochs, the network gets accurate enough for reliable classification.

VI. Recommendation

The dataset may have been shot at a consistent lighting (24W), the lighting may vary when acquired in a different setting. Hence it is recommended to include a white balance chart along with the subject and use a single reference for the lighting by adjusting the white point of the acquired images.

In addition, a higher accuracy can be achieved by feeding more training data to the neural network.

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