IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁜ Impact Factor 7.105 ⁜ Vol. 9, Issue 7, July 2022

DOI: 10.17148/IARJSET.2022.9725

GREEN COFFEE BEANS DEFECTS DETECTION USING CONVOLUTION NEURAL NETWORKS

Rachana V Murthy[1], Vishnu P N [2], Prajwal Nidoni[3], Navyashree M[4], Kiran Kumar[5]

[1]Department of ISE, AMC Engineering College, Bengaluru, Karnataka, India-560083

[2-5]Information Science Engineering, AMC Engineering College, Bangalore, Karnataka

Abstract- The coffee is one of the most important product for the acquisition of foreign currency. The quality of a coffee bean is determined by several factors including color, texture, and size. High quality beans are carefully refined where defects, such as black beans, are removed. The assessment through visual inspection may be subjected to external factors such as light and the amount of beans to be inspected. This study presents a method of controlling the coffee bean quality using Image Processing techniques. Due to its massive trading in world markets, maintaining the quality of coffee is vital for the exporting countries. One approach for quality control is to have a system that can classify coffee beans based on the quality. This system can assist the small-medium coffee enterprises to monitor and secure their procurement. However, the coffee beans quality classification technology is currently unavailable to the small-medium coffee enterprises community. To address this issue, we developed a mobile application powered by a deep-learning-based model to automatically classify coffee beans quality via a mobile phone camera. The deep learning model used is chosen between AlexNet and VGG19 based on their performance to classify coffee beans quality.

Keywords: Coffee, Coffee Beans, classification, deep learning, Image Processing, Defect, convolutional neural network, deep neural network, CNN, Image Processing, artificial neural network.

INTRODUCTION

Coffee is one of the largest agricultural commodities in world markets. In fact, it is the second-largest general commodity after petroleum. Given its significance in world markets, exporting countries need to monitor the quality of their coffee beans. Unfortunately, with the huge trading size, maintaining a good coffee beans quality control is challenging. For efficient monitoring, it is vital to utilize computerized systems for more quality control automation.

The most straightforward approach to exploit a computerized system for coffee beans quality control is to take the picture of the coffee beans and let the system grades them based on the visual. This approach is practical since the emergence of Deep Learning which is powerful in classifying images. It is also the method of preference for other computer vision tasks, as opposed to the traditional method that relies on feature extraction algorithm such as SIFT, SURF, PCA, and LDA. The coffee drink undergoes a meticulous process in order to achieve a great quality. There are several factors which affect the quality like the process on how the coffee is grown and harvested and how the fields

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are processed. Deficiencies in nutrients and use of inadequate protection against coffee diseases will lead to lower quality coffees.

Considering the superiority of Deep Learning, we aimed to use it to help small-medium coffee enterprises to quickly identify the quality of coffee beans. With that capability, they can avoid being scammed to buy coffee beans which quality does not match their preference. To facilitate that, in this study, we developed a mobile application that utilizes Deep Learning for classifying coffee beans quality. Mobile application was chosen as the media because of its high penetration rate in the small-medium enterprises community. This mobile application is called as Cafeon in this paper. The degree of coffee fruit maturation and avoiding mold contamination during harvesting, drying, and storage of the seeds are especially critical. Drying the seeds then removing the fruity parts from the seeds are the two crucial steps to the ultimate quality and character of the coffee. Knowing that some of these precious coffee beans are defective lessen its quality, one of these defects is called the black beans. Black beans typically result from harvesting immature cherries or by harvesting dead cherries that fall naturally from the tree. Black beans can also result from exposure to water, heat and insect-damage.

BACKGROUND

Many researchers have studied methods of automatically classifying the quality of raw coffee beans. Faridah et al. used texture analysis and RGB color information to extract the characteristics of coffee beans, and they trained a neural network for classification using the data. Turi et al. combined color, morphology, and texture data with an artificial neural network (ANN) to identify the species and region of origin of Ethiopian coffee beans. This method successfully classified four coffee beans from different regions. Lab color measurement values based on Commission Internationale d'Eclairage (CIE) have been used as features, and ANN and Bayesian classifiers (Bayes classifiers) have been applied for the quality classification of raw beans. As convolutional neural networks (CNNs) are efficient in image feature extraction, classification, object inspection, and so forth, deep CNNs are applied in the field of image processing

Thus, several researchers have tried to use a CNN to assess the quality of coffee beans. Huang et al. used a CNN to process images of coffee beans and analyze image information. Pinto et al. applied a CNN to classify six different types of defective beans. In hyperspectral signals were processed by using a support vector machine and a CNN to find and classify insect-eaten and rotten beans.

A CNN shows good performance in image classification or recognition but has high computational complexity. As a CNN requires large storage space and computing resources, it cannot be used on mobile devices or embedded platforms. This problem must be solved to implement a smart coffee bean inspection system. Although deep neural networks (DNNs) have been successfully applied in many applications, the complex operation process does not ensure reliability. As neural layers become deeper and more complex, the process becomes more difficult for a human to understand. Therefore, it is not easy to effectively apply a DNN. Despite their high degree of regularity, DNNs sometimes produce unpredictable results, potentially causing errors. This requires an understanding of the internal mechanism by which DNNs make decisions.

EXISTING SYSTEM

In the existing system, first, the image is acquired by using Sony DCS-800 20.1 Megapixels Camera digital camera and stored for later processing using Laptop Computer with the following specifications, Intel Core i7-6700HQ up to 3.5 GHz, 4 GB RAM and 1 TB hard disk capacity with Microsoft window 10 professional, 64 bit operating system using the trial version of MATLAB R2018a platform. The snapshots of the Robusta coffee bean samples were taken by placing the samples on a white background.

The MATLAB (trial version R2018a) image processing toolbox was used to develop a computer routine algorithm to preprocess and extract features of coffee samples images. Next step in the existing system was color feature extraction. The authors gathered the RGB values by using impixel function. Impixel displays the RGB values of the selected pixel. The values that were gathered in RGB extraction were tabulated using the Microsoft Excel Then the third step was training and testing. The 180 coffee beans were grouped into two major groups, the training group and the testing group. There are 70 normal beans and 50 black beans used for training and for testing 35 normal beans and 25 black beans were used for testing. The training group was used to get the RGB value range for both the normal beans and the black beans.

LITERATURE REVIEW

Minaei et al. used classification based on computer vision and expert system for assessing saffron quality. For wheat grains, the classification was dominated by the use of Artificial Neural Network (ANN). Meanwhile, Support Vector

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Machine was utilized for classifying corn kernels grade.

Anagnostis et al. exploited the use of CNN to identify infection of anthracnose in walnut tree leaves. Specifically, for coffee beans, the classification algorithms had been employed to assess their quality and. In these studies, the prevailing modality is visual, hence computer-vision-based algorithms were employed. Some of these studies still applied traditional computer vision techniques. On the other hand, newer studies on coffee beans quality assessment tend to use Deep Learning, which is known to be superior to the traditional computer vision method. In these studies, the exploited visual cues were mostly the color or visible defect. Moreover, the classification algorithms were also used for coffee beans roasting level assessment. The classes used in this case are commonly divided based on these four categories: light roasts, medium roasts, medium-dark roasts, and dark roasts. Similar to other agricultural commodities, the classification algorithm for coffee beans is recently shifted to the use of a CNN-based algorithm.

Faridah et al.used texture analysis and RGB color information to extract the characteristics of coffee beans, and they trained a neural network for classification using the data.

Turi et al. combined color, morphology, and texture data with an artificial neural network (ANN) to identify the species and region of origin of Ethiopian coffee beans. This method successfully classified four coffee beans from different regions. Lab color measurement values based on Commission Internationale d'Eclairage (CIE) have been used as features, and ANN and Bayesian classifiers (Bayes classifiers) have been applied for the quality classification of raw beans. As convolutional neural networks (CNNs) are efficient in image feature extraction, classification, object inspection, and so forth, deep CNNs are applied in the field of image processing.

Livramento et al reported a study on the proteomic analysis of coffee grains exposed to different drying process. The objective of the study is to analyse the proteomic profile and identify differentially abundant proteins in coffee arabica L. grains subjected to two different drying conditions. The samples of coffee grains were collected from the municipality of BomSucesso, state of Minas Gerais, Brazil, from a plot at 1100 m altitude. Two different drying methods are natural coffee and pulped coffee dried with mechanical hot air drying at 60o C.

It is observed that fruits dried in a dryer at 60 C showed an altered proteomic profile, with a reduction in the most abundant proteins compared to those yard-dried grains. The results show that post-harvest processes of the coffee quality are related to changes in protein abundance, indicating that proteomic analysis may be effective in the identification of biochemical changes in coffee grains subjected to different post-harvest processes. The study concluded that drying has been considered as one of the factors that cause impact on the final beverage quality.

Putranto et al proposed reaction engineering (REA) approach to develop mathematical modelling ofintermittent and convective drying of coffee. Results show that the REA models the drying kinetics of coffee with well agreement between predicted and experimental data. The comparison with diffusion-based model, it is claimed the REA perform comparably or even better.

Hernandez-Diaz et al reported a study on modelling heat and mass transfer during drying of green coffee beans using prolate spheroidal geometry. Three-dimensional governing equation in prolate spheroidal coordinate system was solved numerically. The objective was to describe the drying of green coffee beans. The results showed that the method can provide valuable information about the moisture distribution profiles inside the grain during drying. It is suggested to use the model to design the optimal design of coffee driers

.

Ishwarya and Anandharama krishnan reported a study on spray-freeze-drying (SFD) approach for soluble coffee processing and its effect on quality characteristics. The SFD method is compared with spray-dried (SD) and freeze-dried (FD) methods. The analysed qualities are aroma, volatile, solubility, morphology, flow properties and colour measurement. The results show that different drying technique can affect the quality of the dried coffee. In their study, SFD technique can be potentially employed for the production of soluble coffee with improved product characteristics.

Keinwachter and Selmar investigated the influence of drying on the content of sugars in wet processed green Arabica coffees. It is well known that sun drying yields much better green coffee quality than machine drying. However, this conclusion was made based only on traditional knowledge and experience. Thus, the objective of their research is to elucidate the reasons for the putative quality differences between sun and machine dried green coffees. Two different drying methods are compared. The first method is continuous drying and the second method is pause method to mimic day-and-night-rhythm. The comparison quality is carbohydrates content in dried coffee.

Nilnont et al performed finite element simulation for coffee drying to describe moisture diffusivity, shrinkage, equilibrium moisture content. It was shown that the mean diffusivity value of the coffee bean is 1.173 10 10□ □ m2/s. The shrinkage of coffee bean is a linear function of moisture removal.

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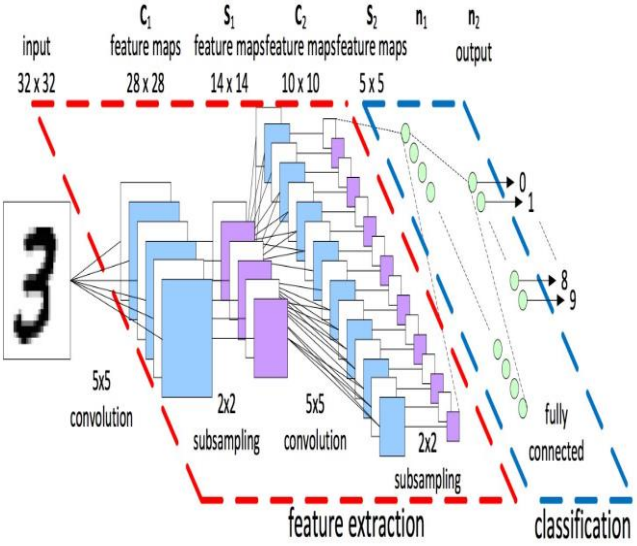
Suzihaque and Driscoll investigated the effect of solar radiation, buoyancy of air flow and optimization study of coffee drying in heat recovery drier. The objective was to develop an efficient heat recovery dryer and to investigate its performance so as to optimize design parameters.

PROPOSED SYSTEM

Convolutional Neural Network (CNN) were used to achieve some breakthrough results and win well-known contests. The application of convolutional layers consists in convolving a signal or an image with kernels to obtain feature maps. So, a unit in a feature map is connected to the previous layer through the weights of the kernels. The weights of the kernels are adapted during the training phase by back propagation, in order to enhance certain characteristics of the input. Since the kernels are shared among all units of the same feature maps, convolutional layers have fewer weights to train than dense FC layers, making CNN easier to train and less prone to overfitting. Moreover, since the same kernel is convolved over all the image, the same feature is detected independently of the locating translation invariance. By using kernels, information of the neighborhood is taken into account, which is an useful source of context information. Usually a non-linear activation function is applied on the output of each neural unit. If we stack several convolutional layers, the extracted features become more abstract with the increasing depth. The first layers enhance features such as edges, which are aggregated in the following layers as motifs, parts, or objects.

SYSTEM ARCHITECTURE



Convolutional Neural Networks architecture

Convolutional Neural Network (CNN) were used to achieve some breakthrough results and win well-known contests. The application of convolutional layers consists in convolving a signal or an image with kernels to obtain feature maps. So, a unit in a feature map is connected to the previous layer through the weights of the kernels. The weights of the kernels are adapted during the training phase by back propagation, in order to enhance certain characteristics of the input. Since the kernels are shared among all units of the same feature maps, convolutional layers have fewer weights to train than dense FC layers, making CNN easier to train and less prone to overfitting. Moreover, since the same kernel is convolved over all the image, the same feature is detected independently of the locating—translation invariance. By using kernels, information of the neighborhood is taken into account, which is an useful source of context information. Usually, a non-linear activation function is applied on the output of each neural unit. If we stack several convolutional layers, the extracted features become more abstract with the increasing depth. The first layers enhance features such as edges, which are aggregated in the following layers as motifs, parts, or objects.

Advantages of algorithm

- Minimize computation compared to a regular neural network.
- Convolution simplifies computation to a great extent without losing the essence of the data.
- They are great at handling image classification.

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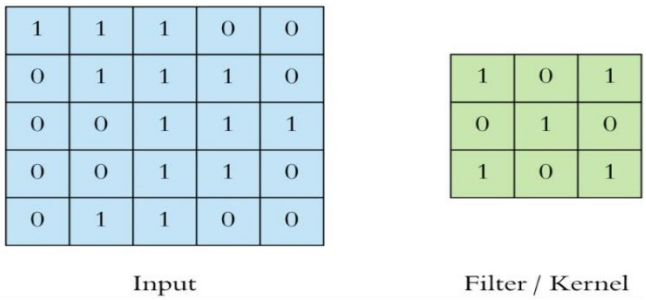
- They use the same knowledge across all image locations.
- Execution time is less.
- Achieves a much better performance using AlexNet.
- High prediction accuracy.

Algorithm working Steps:

Step1: Convolutional Neural Networks
Convolutional Neural Networks have a different architecture than regular Neural Networks. Regular Neural Networks transform an input by putting it through a series of hidden layers. Every layer is made up of a set of neurons, where each layer is fully connected to all neurons in the layer before. Finally, there is a last fully-connected layer — the output layer — that represent the predictions.

Convolutional Neural Networks are a bit different. First of all, the layers are organised in 3 dimensions: width, height and depth. Further, the neurons in one layer do not connect to all the neurons in the next layer but only to a small region of it. Lastly, the final output will be reduced to a single vector of probability scores, organized along the depth dimension.

Step2: Feature Extraction: Convolution:
Convolution in CNN is performed on an input image using a filter or a kernel. To understand filtering and convolution you will have to scan the screen starting from top left to right and moving down a bit after covering the width of the screen and repeating the same process until you are done scanning the whole screen.
For instance if the input image and the filter look like following:



Input image and the filter

The filter (green) slides over the input image (blue) one pixel at a time starting from the top left. The filter multiplies its own values with the overlapping values of the image while sliding over it and adds all of them up to output a single value for each overlap until the entire image is traversed.

Step3: Feature Extraction: padding
There are two types of results to the operation — one in which the convoluted feature is reduced in dimensionality as compared to the input, and the other in which the dimensionality is either increased or remains the same. This is done by applying Valid Padding or Same Padding in the case of the latter. In above example our padding is 1.

In our example when we augment the 5x5x1 image into a 7x7x1 image and then apply the 3x3x1 kernel over it, we find that the convoluted matrix turns out to be of dimensions 5x5x1. It means our output image is with same dimensions as our output image (Same Padding).

On the other hand, if we perform the same operation without padding, in the output we'll receive an image with reduced dimensions. So our (5x5x1) image will become (3x3x1).
Feature Extraction: example,

Lets say we have a handwritten digit image like the one below. We want to extract out only the horizontal edges or lines from the image. We will use a filter or kernel which when convoluted with the original image dims out all those areas which do not have horizontal edges.

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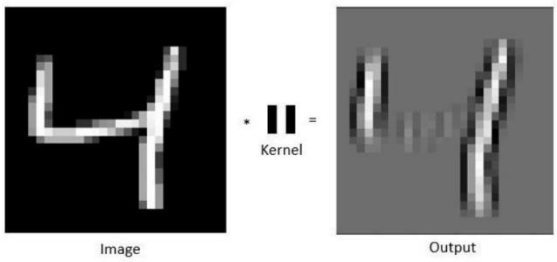
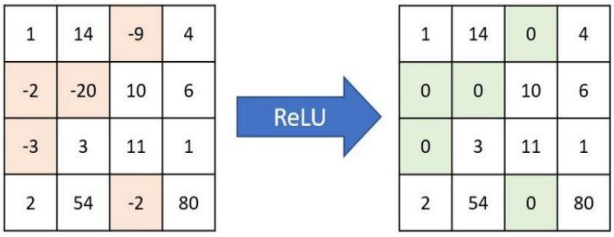
Notice how the output image only has the horizontal white line and rest of the image is dimmed. The kernel here is like a peephole which is a horizontal slit. Similarly for a vertical edge extractor the filter is like a vertical slit peephole and the output would look like



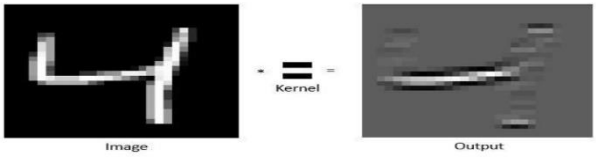
Vertical filter example

Step4: Feature Extraction: Non-Linearity

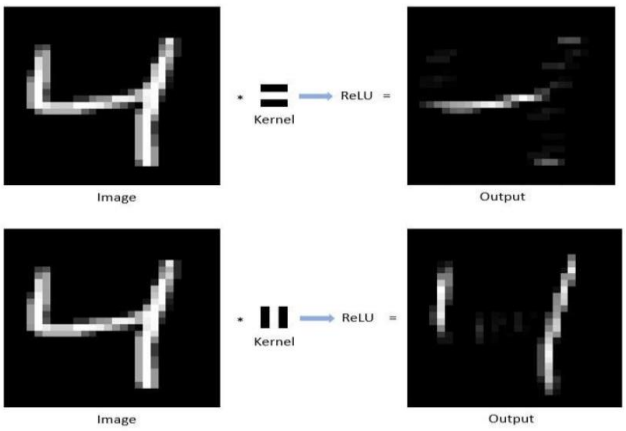
After sliding our filter over the original image the output which we get is passed through another mathematical function which is called an activation function. The activation function usually used in most cases in CNN feature extraction is ReLu which stands for Rectified Linear Unit. Which simply converts all of the negative values to 0 and keeps the positive values the same



CNN feature extraction with ReLu



After passing the outputs through ReLu functions they look like,



Input image after filters with ReLu example

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So for a single image by convolving it with multiple filters we can get multiple output images. For the handwritten digit here we applied a horizontal edge extractor and a vertical edge extractor and got two output images. We can apply several other filters to generate more such outputs images which are also referred as feature maps.

Step5: Feature Extraction: Pooling

After a convolution layer once you get the feature maps, it is common to add a pooling or a sub-sampling layer in CNN layers. Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to decrease the computational power required to process the data through dimensionality reduction. Furthermore, it is useful for extracting dominant features which are rotational and positional invariant, thus maintaining the process of effectively training of the model. Pooling shortens the training time and controls over-fitting.

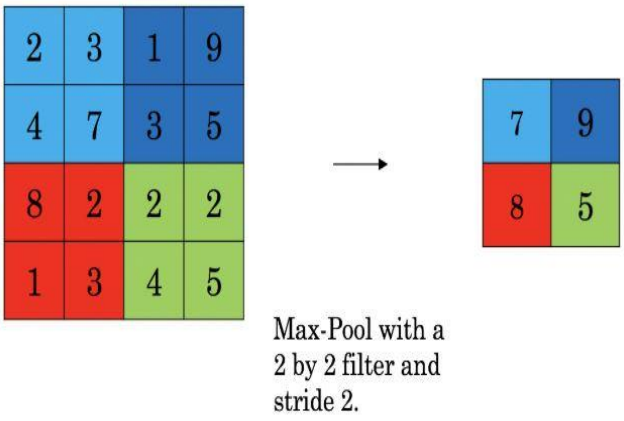
There are two types of Pooling:

Max Pooling and Average Pooling. Max Pooling returns the maximum value from the portion of the image covered by the Kernel. Max Pooling also performs as a Noise Suppressant. It discards the noisy activation altogether and also performs de-noising along with dimensionality reduction.

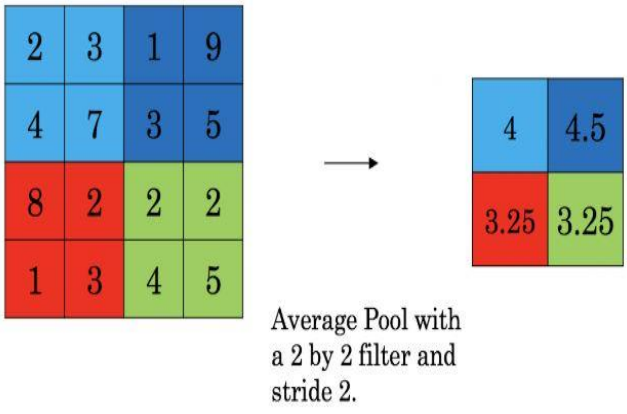
Average Pooling returns the average of all the values from the portion of the image covered by the Kernel. Average Pooling simply performs dimensionality reduction as a noise suppressing mechanism. Hence, we can say that Max Pooling performs a lot better than Average Pooling.

The Convolutional Layer and the Pooling Layer, together form the i-th layer of a Convolutional Neural Network. Depending on the complexities in the images, the number of such layers may be increased for capturing low-levels details even further, but at the cost of more computational power.

After going through the above process, we have successfully enabled the model to understand the features. Moving on, we are going to flatten the final output and feed it to a regular Neural Network for classification purposes.



Max Pooling example



Average Pooling example

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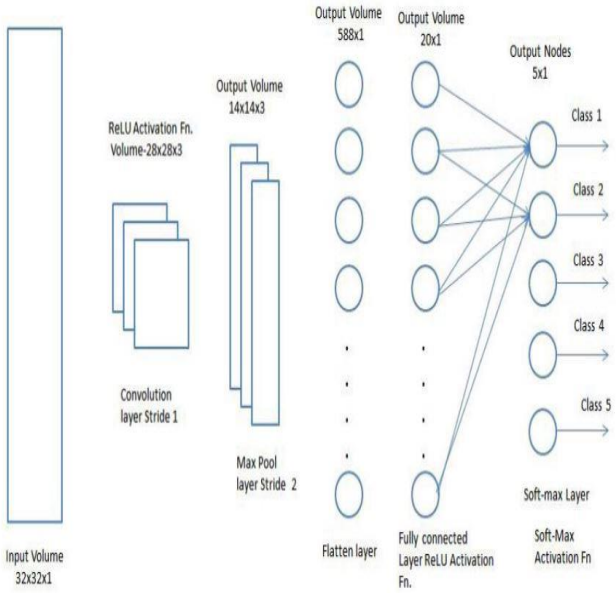
Step6: Classification — Fully Connected Layer (FC Layer):

Adding a Fully-Connected layer is a (usually) cheap way of learning non-linear combinations of the high-level features as represented by the output of the convolutional layer. The Fully-Connected layer is learning a possibly non-linear function in that space. Example of CNN network:



Fully Connected model

Now that we have converted our input image into a suitable form, we shall flatten the image into a column vector. The flattened output is fed to a feed-forward neural network and back propagation applied to every iteration of training. Over a series of epochs, the model is able to distinguish between dominating and certain low-level features in images and classify them using the Softmax Classification technique.

So now we have all the pieces required to build a CNN. Convolution, ReLU and Pooling. The output of max pooling is fed into the classifier which is usually a multi-layer perceptron layer. Usually in CNNs these layers are used more than once i.e. Convolution -> ReLU -> Max-Pool -> Convolution -> ReLU -> Max-Pool and so on.

RESULT

In this experiment, the front-side and back-side coffee bean images for both normal and defects 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 ‘defets’ and ‘healthy’ regardless of front-side or back-side, assuming the practical use. This experiment was a preliminary experiment for the whole system we will develop. The system must classify the ‘healthy’ and ‘defects’ regardless of the sides. In this work, we evaluated the performance and examined using different architectures of convolutional neural networks (CNN).

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In some case, Fade and Sour are shown simultaneously on the bean and in some case Fade bean has a good appearance. Therefore, it was difficult to detect the difference between Fade and Sour and also Fade and normal beans during labeling which can affect the result of the CNN.

In this study, the broken bean and peaberry also have low accuracy, it might be caused by the number of samples was too small and then at the same time they also had other characteristics of another defect type which difficult to classify correctly by CNN model. In the case of broken bean, not only detected base on color but also detected through damaged on the bean surface or part of the bean lost. Similar case of the broken bean, the peaberry has other important feature to detect by the shape of bean. The peaberry has a single rounded bean rom a coffee cherry instead of the usual flat sided pair of beans. In this work we compare the original color image with the gray scale image of the broken and the peaberry after applied some basics image processing technique. However, the result in Table V shown that the color one is presently higher than the gray image in the classification accuracy. So the image processing technique did not improve the classification accuracy. On the other hand, the classification accuracy is low might be caused by the CNN model could not suitable to extract the feature of coffee bean images because insufficient of image data.

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```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 54, 54, 96)        34944

 max_pooling2d (MaxPooling2D  (None, 27, 27, 96)       0
 )

 batch_normalization (BatchN  (None, 27, 27, 96)       384
 ormalization)

 conv2d_1 (Conv2D)           (None, 23, 23, 256)       614656

 max_pooling2d_1 (MaxPooling  (None, 11, 11, 256)      0
 2D)

 batch_normalization_1 (Batc  (None, 11, 11, 256)      1024
 hNormalization)

 conv2d_2 (Conv2D)           (None, 9, 9, 512)         1180160

 batch_normalization_2 (Batc  (None, 9, 9, 512)        2048
 hNormalization)

 conv2d_3 (Conv2D)           (None, 7, 7, 1024)        4719616

 batch_normalization_3 (Batc  (None, 7, 7, 1024)       4096
 hNormalization)

 conv2d_4 (Conv2D)           (None, 5, 5, 1024)        9438208

 max_pooling2d_2 (MaxPooling  (None, 2, 2, 1024)       0
 2D)

 batch_normalization_4 (Batc  (None, 2, 2, 1024)       4096
 hNormalization)

 flatten (Flatten)           (None, 4096)              0

 dense (Dense)               (None, 4096)              16781312

 dropout (Dropout)           (None, 4096)              0

 batch_normalization_5 (Batc  (None, 4096)             16384
 hNormalization)

 dense_1 (Dense)             (None, 4096)              16781312

 dropout_1 (Dropout)         (None, 4096)              0

 batch_normalization_6 (Batc  (None, 4096)             16384
 hNormalization)

 dense_2 (Dense)             (None, 1000)              4097000

 dropout_2 (Dropout)         (None, 1000)              0

 batch_normalization_7 (Batc  (None, 1000)             4000
 hNormalization)

 dense_3 (Dense)             (None, 2)                 2002

=================================================================
Total params: 53,697,626
Trainable params: 53,673,418
Non-trainable params: 24,208
```

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```
Epoch 1/10
20/20 [==============================] - ETA: 0s - loss: 1.8766 - accuracy: 0.5895
Epoch 1: val_loss improved from inf to 202.42088, saving model to weights.hdf5
20/20 [==============================] - 204s 10s/step - loss: 1.8766 - accuracy: 0.5895 - val_loss: 202.4209 - val_accuracy: 0.4766 - lr: 0.0010
Epoch 2/10
20/20 [==============================] - ETA: 0s - loss: 0.6673 - accuracy: 0.6862
Epoch 2: val_loss did not improve from 202.42088
20/20 [==============================] - 186s 9s/step - loss: 0.6673 - accuracy: 0.6862 - val_loss: 352.5986 - val_accuracy: 0.4727 - lr: 0.0010
Epoch 3/10
20/20 [==============================] - ETA: 0s - loss: 0.5791 - accuracy: 0.7006
Epoch 3: val_loss improved from 202.42088 to 20.59789, saving model to weights.hdf5
20/20 [==============================] - 185s 9s/step - loss: 0.5791 - accuracy: 0.7006 - val_loss: 20.5979 - val_accuracy: 0.4688 - lr: 0.0010
Epoch 4/10
20/20 [==============================] - ETA: 0s - loss: 0.5577 - accuracy: 0.7023
Epoch 4: val_loss did not improve from 20.59789
20/20 [==============================] - 193s 10s/step - loss: 0.5577 - accuracy: 0.7023 - val_loss: 38.5271 - val_accuracy: 0.4844 - lr: 0.0010
Epoch 5/10
20/20 [==============================] - ETA: 0s - loss: 0.5439 - accuracy: 0.7035
Epoch 5: val_loss improved from 20.59789 to 2.29077, saving model to weights.hdf5
20/20 [==============================] - 198s 10s/step - loss: 0.5439 - accuracy: 0.7035 - val_loss: 2.2908 - val_accuracy: 0.6797 - lr: 0.0010
Epoch 6/10
20/20 [==============================] - ETA: 0s - loss: 0.5162 - accuracy: 0.7240
Epoch 6: val_loss improved from 2.29077 to 1.78325, saving model to weights.hdf5
20/20 [==============================] - 186s 9s/step - loss: 0.5162 - accuracy: 0.7240 - val_loss: 1.7832 - val_accuracy: 0.4805 - lr: 0.0010
Epoch 7/10
20/20 [==============================] - ETA: 0s - loss: 0.5679 - accuracy: 0.6743
Epoch 7: val_loss did not improve from 1.78325
20/20 [==============================] - 186s 9s/step - loss: 0.5679 - accuracy: 0.6743 - val_loss: 4.4620 - val_accuracy: 0.5469 - lr: 0.0010
Epoch 8/10
20/20 [==============================] - ETA: 0s - loss: 0.5243 - accuracy: 0.7224
Epoch 8: val_loss did not improve from 1.78325
20/20 [==============================] - 185s 9s/step - loss: 0.5243 - accuracy: 0.7224 - val_loss: 5.6135 - val_accuracy: 0.4961 - lr: 0.0010
Epoch 9/10
20/20 [==============================] - ETA: 0s - loss: 0.5210 - accuracy: 0.7150
Epoch 9: val_loss improved from 1.78325 to 0.37413, saving model to weights.hdf5
20/20 [==============================] - 186s 9s/step - loss: 0.5210 - accuracy: 0.7150 - val_loss: 0.3741 - val_accuracy: 0.8516 - lr: 0.0010
Epoch 10/10
20/20 [==============================] - ETA: 0s - loss: 0.5377 - accuracy: 0.7265
Epoch 10: val_loss did not improve from 0.37413
20/20 [==============================] - 190s 9s/step - loss: 0.5377 - accuracy: 0.7265 - val_loss: 3.6414 - val_accuracy: 0.5312 - lr: 0.0010
```

```
predict('a.png')

Detected:


1/1 [==============================] - 3s 3s/step
>>>> [0]
0 0
1/1 [==============================] - 0s 52ms/step
img_class [[9.997160e-01 2.839811e-04]]
class_name Defect
Defect
```

CONCLUSION

This study explored the importance of the coffee industry in countries including Brazil, Vietnam, Colombia, Indonesia, Ethiopia, Honduras, India, Peru, and Uganda. As coffee is a major export product that drives the country's economy, research on coffee beans quality is essential to maintain market competitiveness. In this sense, random forest was introduced in this study to predict coffee quality. As a result, the deep learning model performed best, with an accuracy of 94.7%. In addition, the most important variables when predicting coffee quality were found to be the types of coffee

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁜ Impact Factor 7.105 ⁜ Vol. 9, Issue 7, July 2022

DOI: 10.17148/IARJSET.2022.9725

beans defects, coffee beans healthiness. Since coffee beans quality prediction using deep learning enables coffee-producing countries to produce high-quality coffee, their competitiveness in the market will ultimately bring sustainable social and economic development to their society and country.

FUTURE WORK

In future we will like to study the stages of the coffee beans in which the best quality of coffee beans can be produced. Along with the healthy and defects we will focus of the quality.

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