Computer Aided System for Gambung Tea Identification using Convolutional Neural Network

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Abstract. Tea commodity has a very strategic role for Indonesian economy. In 2012 the tea commodity was able to generate foreign exchange of US $ 156.74 million. Nationally, tea industry contributes a Gross Domestic Product (GDP) of around Rp. 1.2 trillion. The total tea plantation area in Indonesia entirely covering 123,938 hectares. The conception of sustainable tea production includes three aspects, economic development, social development and environmental protection. One of the steps towards sustainable tea production is survey and identification. The process continues with the selection of suitable planting material (seedlings). Gambung series, are planting material seeds that have been recommended by the Indonesia Ministry of Agriculture. The Gambung series has a potential yield of 4,000 - 5,800 kg/hectare of dried tea. The morphological similarity level of Gambung series is very high, because the elders of the clones are from the same crossing parents. Experts who are able to identify Gambung clone are very limited. This process is susceptible to errors and is very dependent on the presence of experts. If an error occurs in the process of identifying the type of clone, it will interferes with the breeding process. Errors in the selection of recommended clones will be detrimental to the process for long time period, due to the economic age of the tea plant can reach 50 years. From this issue, it is very necessary to design a system that is able to identify the planting material of Gambung series clones. The system is designed to classify Gambung and Non Gambung tea series using Convolutional Neural Network (CNN) with a high accuracy and low loss rate.

1. Introduction

Indonesia has been known as one of foremost tea producers in the world. Tea is a commodity from the plantation sector which has experienced a triumph over the past decades. But from year to year, Indonesia’s tea ranking in the international market continues to decline [1]. The geographical location of Indonesia which is on the equatorial trajectory and the presence of hundreds volcanoes are the main factors causing Indonesia’s fertile soil. The fertile soil are suitable for the conditions for growing tea and has great potential to expand the land and increase the quantity and quality of tea Indonesia [2]. In addition to the increasingly export opportunities, the domestic tea market is still quite large even though it has not been optimally explored yet. Tea plantations in Indonesia are distinguished according to their operations became Perkebunan Besar (PB) and Perkebunan Rakyat (PR). Perkebunan Besar consist of Perkebunan Besar Negara (PBN) and Perkebunan Besar Swasta (PBS). In 2016, the area of PBN was recorded experiencing decreased by 5.29% and continued to decline until 2018 decreased by 15.39%. While the total area of PBS in 2016 decreased by 1.92% and in 2018 decreased...
again by 6.71% [3]. This land reduction are caused by several things, one of is due to the favorable business prospects of oil palm, so that tea plantations have been converted into oil palm plantations. It was also caused by some tea plantations was stop the production and switch to more profitable commodities. Mistakes in selecting superior seedlings are one causes of decreased productivity of tea plants.

Figure 1. Development of Indonesia’s Tea Plantation Area in the 2016 - 2018 Period [3]

One of the steps towards sustainable tea production is survey and identification. The survey was conducted to determine the condition related to: soil, biodiversity, social and human resources. After knowing the survey results, identification of deficiencies can be more easily done. This is useful to determine the direction and priority of improvement towards sustainable tea plantations, one of which is election suitable planting material (seeds). Based on the Decree of the Indonesian Minister of Agriculture, the Gambung series superior clones have been released. Gambung series has a potential yield of 4000 - 5800 kg / hectare of dry tea. During this time, the process of identifying gambung series is done manually using visual eyes of experts at PPTK Gambung. This process is susceptible to errors in the reading of clone types, and is very dependent on the presence of experts. If an error occurs in the process of identifying the type of Gambung series clone, would certainly would be detrimental to the production process for many years. Errors in the selection of Gambung series clone plant material will have a long-term loss due to the economic life of the tea plant which can reach 50 years. The potential loss of production in an area of 127357 hectare due to misuse of plant material can reach 1200 kg/hectare/year or equivalent to loss of potential income of Rp. 30 billion/year (assuming the selling price of dry tea is Rp. 20000/kg). From this issue, it is very necessary to design a system that is able to identify Gambung series clones. The system is designed to classify Gambung and Non Gambung tea series using Convolutional Neural Network (CNN).

There are several identification systems using leaf recognition that have been developed by several previous researchers. However, most of the leaves data-set are originating from abroad plants. So, it is not necessarily suitable when used to detect leaves plants from Indonesia. Hossain and Amin [4] developed a system that was able to detect 30 types of leaves from different plants. The system consists of 5 main processes, images are taken from a digital camera or scanner, the selection of leaf base points and several other reference points, separating leaves from the background and converting the RGB into a binary images, equalizing the leaf with the base point, and extraction of leaf morphological features. After that, the results of feature
extraction are used as input in classification processes using a Probabilistic Neural Network (PNN). From the testing results of 1200 samples (30 different plants), system was able to identify the type of leaf with an accuracy of 91.41%. Kumar, et al [5] proposed a smartphone application to identify plant types by using leaves visual recognition. The methods are separating non-leaf imagery, segmentation of leaves from non-textured backgrounds, extraction of curvature features, and classification using the K-Nearest Neighbor. The system uses data sets of 184 plants in Northeastern United States. Unfortunately there are no reports on how accurate the testing of this system is. Aakif and Khan [6] created a system of identifying 14 different fruit plants. The method used consists of 3 main steps, pre-processing, feature extraction and classification. Features extracted including morphological features, fourier descriptors, and shapes. The classification used is artificial neural network (ANN). From the testing/validation process of 817 samples, the results give an accuracy of 96%. Research related to the classification of leaves-based plants using CNN has been carried out by Lee, et al [7] and Syamsul et al [8]. Lee developed a leaf identification system using the Convolutional Neural Network (CNN) classification method, with feature selection made using the Deconvolutional Network (DN) approach. This system was tested on MalayaKew (MK) Leaf dataset consisting of 44 different plant species. The accuracy of the system validating is 98.1%. Syamsul has been built a system using CNN with 3 hidden layers plus a fully connected layer with softmax activation to determine its classification [8]. After doing the training and validation process for 50 iterations, obtained 86% accuracy and loss of 0.087. Suyanto and Munte [9] proposed a system that could identify the type of rubber plant from the leaves. The methods used in the system are data acquisition, image processing, edge detection using Sobel, and identification using template matching. System testing was carried out using 14 rubber clones in the White Sungei Rubber Research Center. From the test results it can be seen that the accuracy of this system is 91.79%. Turkoglu and Hanbay [10] developed a plant identification system using leaf recognition. Feature extraction used is color features, leaf bone, Fourier Descriptor (FD), and Gray-Level-Co-occurance (GLCM). Next, the classification method used is Extreme Learning Machines (ELM). This system was tested on Flavia dataset, the test results found that this system has an accuracy of 99.10%.

Reviewing some of the previous research above, then we propose a system that is able to identify Indonesia’s superior tea plants, Gambung tea series. We propose a system using Convolutional Neural Network (CNN) modeling. Nowadays, CNN has been widely used in various applications, especially for images and videos processing. CNN will continue to practice learning filters by itself without explicit mentioning it.

2. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is one of the deep learning methods that designed to process images (two-dimensional) data [11]. The Convolutional Neural Network is a development of back-propagation method that composed of several layers namely input layer, followed by several hidden layers and output layers [12].
Figure 2. The Architecture of CNN

At each layer is composed of several neurons that are connected to all neurons in the previous layer and the layer afterwards. In order that, CNN imitates the work of visual cortex in the brain to process and to recognize image [12]. The architecture of CNN is shown in Figure 2 as follows [13]. Based on Figure 2, the architecture of CNN consists of two main process namely feature extraction and classification that are connected respectively.

2.1. Feature Extraction

Feature extraction neural network consists of the convolutional layer and the pooling layer. CNN works hierarchically, so the output at the first convolution layer is used as input at the next convolution layer. The convolutional layer uses filter to generate feature maps from input image. The number of feature maps generated depends on the numbers of filters used. Therefore, for instance, if the convolutional contains three filters, it will generate three feature maps [12]. There are parameters that influence the convolutional layer, namely filter size, stride and padding. Stride is useful for determining the shift in the number of filters. Padding or zero padding is a parameter that determines the number of pixels (containing the value 0) to be added to each side of the image with the aim of accurate information on the edges of the image. An illustration of the convolution process is shown in Figure 3.

Figure 3. Convolutional process of input data with size 4 and stride 1(a), filter size (2) (b), and result (c)

Rectified Linear Unit (ReLU) is an important element in the convolutional layer to change
the negative pixel value on the feature map to zero. The ReLU activation function is given in Equation 1 as follows [14].

\[ f(x) = \max(0, x) \] (1)

The output value of a neuron can be expressed as 0 if the input is negative. If the input value is positive, then the output of the neuron is the activation input value itself [15].

Pooling or sub-sampling is a reduction in matrix size. There are two types of pooling that are often used, namely average pooling and max pooling [2] The value taken at average pooling is the average value while at max pooling is the maximum value [12]. Figure 4 is shown the illustrate of average pooling and maximum pooling.

![Illustrate of Pooling Layer](image)

**Figure 4.** Illustrate of Pooling Layer, (a). The four by four pixel input image ; (b). Mean Pooling and (c). Maximum Pooling

2.2. Classification

Feature maps as a result of feature learning layer are multidimensional arrays. The flatten process convert feature maps from multidimensional arrays to one dimensional array so after that it can be processed at the fully connected layer. This layer gets input from the previous process to determine which features are most correlated with a particular class [16]. The sigmoid activation function is used to get the classification results. The sigmoid function is used for binary classification in the Logistic Regression model, it transforms the range of values from input x to be between 0 and 1 with the distribution form of the function as in Figure 5 and shown by Equation 2 as follows [17]:

\[ S(x) = \frac{1}{1 + e^{-x}} \] (2)
3. System Design
In this research, the system is built using CNN with two hidden convolutional layer and a fully connected later. Figure 6 and Table 1 show the layer configuration in our CNN model.

Figure 6. Proposed Model of CNN
Table 1. Summary of CNN Configuration

| Layer (type)       | Output Shape      | Parameter |
|--------------------|-------------------|-----------|
| conv2d_1 (Conv2D)  | (None, 64, 64, 8) | 224       |
| activation_1       | (None, 64, 64, 8) | 0         |
| max_pooling2d_1    | (None, 32, 32, 8) | 0         |
| conv2d_2 (Conv2D)  | (None, 32, 32, 16)| 1168      |
| activation_2       | (None, 32, 32, 16)| 0         |
| max_pooling2d_2    | (None, 16, 16, 16)| 0         |
| flatten_1          | (None, 4096)      | 0         |
| dense_1 (Dense)    | (None, 2)         | 8194      |
| activation_3       | (None, 2)         | 0         |

Total parameters: 9,586
Trainable parameters: 9,586
Non-trainable parameters: 0

The Dataset of tea leaves that used in this research is 212 image of training image (consist of 36 image non Gambung tea leaves images and 176 Gambung tea leaves images) 71 of testing images (consist of 27 images for non Gambung tea leaves images and 44 Gambung tea leaves images). Based on Figure 6 and Table 1, the resolution of tea leaves images is changed to 64 × 64 pixel and it inserted into CNN. In hidden layer 1, we use filter with size 3 × 3 and channel output 8. In hidden layer 2, we use filter with size 3 × 3 and channel output 16. After that, we do the flatten to change the image featured from 3 dimension became 1 dimension so that we can do the classification into 2 class (Gambung Tea Class and Non Gambung Tea Class). Activation that used to do the classification is sigmoid.

In the first convolution layer, named conv2d_1 layer, the data images that has been resized to 64 × 64 pixels in three layers (Red, Green, and Blue), will be convoluted by filter with 2 × 2 size, and the output is the 32 × 32 pixels images size with 8 layers. The output from first convolution layer illustrated in figure 7 below.

Figure 7. Output Image of the first convolutional layer with (a). GMB image input and (b). nonGMB image input

These images will go through the second convolutional layer, named conv2d_2 layer, and it will be convoluted by filter with 2 × 2 size, so the output is the 16 × 16 pixels images size with 16 layers. The output from first convolution layer illustrated in figure 8 below.
4. Result and Analysis

Adam with learning rate 0.001 is used for Optimizer, and Binary Crossentropy for loss. The measured parameters is accuracy and loss. Total iteration for training data is 50 times (50 epoch). After do the training, we can see the result of accuracy and loss from Figure 7 and Figure 8 below.

Figure 8. Output Image of the second convolutional layer with (a). GMB image input and (b). nonGMB image input

Figure 9. The Increase of accuracy value in training process and validation process
Figure 9 shows the increase of accuracy value for each iteration (epoch). The model is not over-fitting that we can see from the difference between training accuracy and validation accuracy is not too far. Figure 10 shows the decrease of loss of value for each iteration. The difference between training loss and validation loss is not too far, so we can conclude that the model system can be used to classify between Gambung Tea and non Gambung Tea with the accuracy 100% and loss 0.0007.

5. Conclusion
To classify the Gambung and Non Gambung Series tea leaves, a system has been built using CNN with two hidden layers plus one fully connected layer with sigmoid activation to determine its classification. After doing the 50 iterations for training and validation process, obtained an accuracy value of 100% with 0.0007 loss. So it can be concluded that this system does not occur over-fitting, which means the system can recognize the type of Gambung and Non Gambung tea leaves with new data.

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