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Implementation of Deep Learning Using Convolutional Neural Network Algorithm for Classification Rose Flower

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Abstract. Flora in Indonesia has about 25% of the species of flowering plant species present in the world. Roses are one type of flowering plants and are usually used as an ornamental plant that has a thorny stem. Roses have more than 150 species. In Indonesia there are several flower gardens that is larger than the others. One of the famous flower garden in Indonesia is located on Malang city, East Java. The flower garden in Malang has several varieties of many roses and has a large production of roses. To help the sales system of roses there, the researchers want to create a program that can classify the type of roses in order to help simplify the system of automatic sales of roses without through manual sorting. So that will accelerate the sale of roses with an automated system. Ordinary people with limited botanical knowledge usually don't know how to classify the flowers just by looking at them. To classify the flowers properly, it is important to provide enough information, and one of them is the name of it. Convolutional Neural Network (CNN) is one method of deep learning that can be used for image classification process. The CNN design is motivated by the discovery of the visual mechanism, the visual cortex present in the brain. CNN has been widely used in many real-world applications, such as Face Recognition, Image Classification and Recognition, and Object Detection, because this is one of the most efficient method for extracting important features. In this research, the classification accuracy value obtained from the test data is 96.33% using 2-dimension Red Green Blue (RGB) input image, and the size of each image is 32 x 32 pixels that are trained with CNN algorithm and the network structure of four convolution layers and four layers pooling supported by dropout technique.

1. Introduction

Apart from being known as an agricultural country, Indonesia is also known as one of the countries that has important role in the agricultural sector, because it has strategic location and large area. Based on the data from the Ministry of Environment in 2013, Indonesia has an area of 1.3% of the earth's surface and has high biodiversity (mega biodiversity), which is about 17% of all types of living things on this earth. Indonesian flora is also part of *Malesiana*, because in the plant world Indonesia has about 25% of the species of flowering plant species in the world [14].

Convolutional Neural Network (CNN) is a deep learning method that can be used for image classification process. CNN has been widely used in many applications in the real world, such as face recognition, image recognition and recognition, and object detection because this method is one of the most efficient methods for extracting features, and essential feature with less luminance task. The design



of the Convolutional Neural Network was motivated by the discovery of a visual mechanism, namely the visual cortex in the brain.

Flower classification has a wide range of applications, as it helps in finding the name of flowers in floriculture, automating the floriculture system and more. Based on the above background, this study will implement the implementation of the deep learning method using CNN to classify roses which aims to help introduce several types so that people who do not know the types of roses can find out what types of roses are in the image and the program created can be applied to the flower sales system automatically without asking the seller what the name of the flower is. This study focuses on how to classify the image of roses into several types.

2. Theoretical Basis

2.1. Roses

Roses are one of the cut flowers that are most in demand by the community, where they are often used as decorative flowers at formal events such as seminars, workshops or non-formal events such as weddings and traditional events. The general characteristics of a rose flower are that it grows like a shrub that has a height of approximately 2 meters, has an upright round stems with spiny greenish green, leaves about 5-10 cm long and 1.5-2.5 cm wide, the flowers smell nice and taproot.

2.1.1. Burgundy Red Roses

This Burgundy rose is a red rose which is very popular in the world. This flower has a flower size between 8-10 cm and can bloom more than once a season. This flower is included in the type of Hybrid rose. Burgund flowers have a plant height that ranges from 40-45cm. *Formatting author names* The list of authors should be indented 25 mm to match the abstract. The style for the names is initials then surname, with a comma after all but the last two names, which are separated by 'and'. Initials should not have full stops—for example A J Smith and *not* A. J. Smith. First names in full may be used if desired. If an author has additional information to appear as a footnote, such as a permanent address or to indicate that they are the corresponding author, the footnote should be entered after the surname.



Figure 1. Burgundy Rose (Route10Garden, 2018)

2.1.2. Osiana Roses

This Osiana flower was a popular cut flower from the early 1980s. It is known as a cut flower that grows outdoors and originates in Germany and is known throughout the world. Osiana flowers have a very elegant face, are large and have a fruity fragrance. The size of this flower ranges from 8-10cm. The color of this flower is creamy white and has a plant height of 100-130cm.



Figure 2 Osiana Rose (Rosto4ek, 2018)

2.1.3. *Damascus Roses*

Considered to be one of the oldest roses from Europe, Damascus Rose is also known as Rose of Catile or Damascus Rose. These flowers make a very enchanting choice for a bouquet or bouquet because they have a very strong fragrance. Today, Damascus roses are widely grown throughout Europe. Some of the benefits of this flower are that the petals can be used for making perfume, as a food spice and are widely used in the cosmetic industry. This Damascus rose can be found in the bush that is quite tall, has a soft texture and is quite large. Usually these flowers are pastel pink and some have a strong sweet aroma and have a flower petal length of 3-4 inches.



Figure 3. Damascus Roses (Gramunion, 2018)

2.2. *Imagery*

Image is a representation or description, imitation or similarity of an object. Literally, an image is an image that has a two-dimensional (two-dimensional) plane size. From a mathematical point of view, image is a continuous function of light intensity in a two-dimensional plane. The image comes from the reflection of light that illuminates several objects, then this light reflection is captured by optical devices such as the eye, the camera so that the image of the object is formed as an image that can be recorded. In another sense, the image is the output of a data recording system, one of which is optical in the form of photos, analog in nature, which is in the form of video signals such as images on a television monitor screen and can also be digital which can be stored on a storage medium [26].

Digital Image is an image arranged in the form of a grid, where each box formed is called a pixel and has a two-dimensional function $f(x, y)$ with coordinates (x, y) . The x-axis represents rows and the y-axis represents columns. Each pixel has a value that indicates the color intensity of that pixel. Figure.

2.2.1. *below shows the coordinates of the digital image.*

Digital images are usually written with a matrix of size $N \times M$, where N is the column / height while M is the row / width. There are two parameters that are owned by pixels, namely coordinates and color intensity. The value contained in the coordinates (x, y) is the amount of color intensity of the pixels in

that point. Several formats of digital images are BMP, PNG, JPG, GIF and others (Kusumanto and Tompunu, 2011).

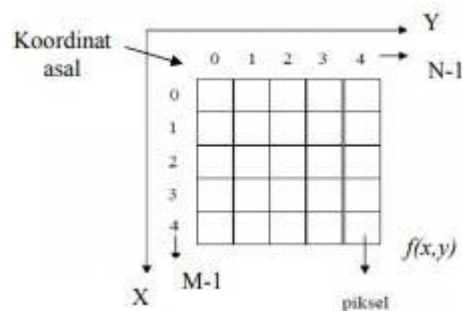


Figure 4. Koordinat Citra Digital (Sutoyo dkk, 2009)

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & \dots & f(0,M-1) \\ f(1,0) & f(1,1) & \dots & f(1,M-1) \\ \vdots & \vdots & \ddots & \vdots \\ f(N-1,0) & f(N-1,1) & \dots & f(N-1,M-1) \end{bmatrix}$$

2.2.2. Convolutional Neural Network

“Convolutional Neural Network (CNN) is a development of Multilayer Perceptron (MLP) which is designed to process two-dimensional data. CNN is included in the type of Deep Neural Network because of its high network depth and is widely applied to image data. In the case of image classification, MLP is not suitable for use because it does not store spatial information from image data and considers each pixel to be an independent feature, resulting in unfavorable results” [2].

The convolutional layer in CNN performs functions that are performed by cells in the visual cortex. In general, the convolutional layer will detect features in the form of edges on the image, then the subsampling layer will reduce the dimensions of the features obtained from the convolutional layer, and finally forward it to the output node through the forward propagation process, and the prediction of the data class is finally determined by the method. Softmax on the dense layer or fully connected layer [12].

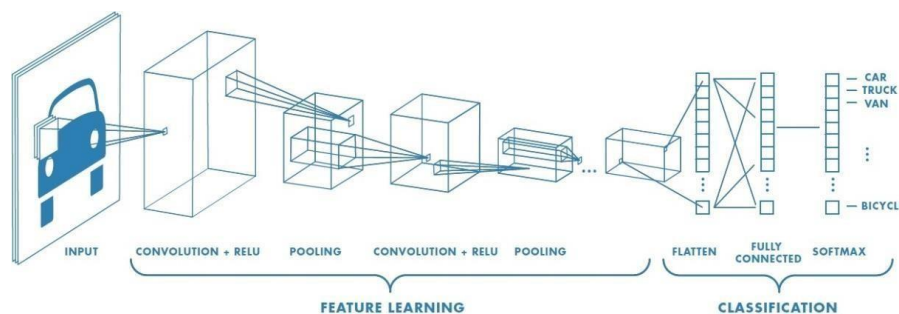


Figure 5. Convolutional Neural Network Architecture (Douglas, 2018)

2.3. Back Propagation Algorithm

The Back-Propagation Algorithm is a popular algorithm used in the training phase of an artificial neural network. According to the Fundamental of Neural Networks book, basically this algorithm is divided into three important stages, namely the forward propagation section, then the back-propagation error section, and finally the weight adjustment section or the weight adjustment phase [3]. The weight referred to in this algorithm is the value contained in the link between neurons in the artificial neural network structure.

In the forward propagation phase, the input layer x will continue the input through the connection v , then enter the hidden layer z , to calculate the input value in the hidden layer, the equation below can be used [3] where i is the index of the input neuron, j is index of hidden neurons and n is the total number of input neurons.

$$z_{in_j} = V_{0j} + \sum_{i=1}^n x_i v_{ij}$$

In this layer the activation value will be calculated with a function of each neuron which will then be forwarded to each neuron in the output layer with equation below :

$$z_j = f(z_{in_j})$$

On the Back-propagation Net, after the criteria for stopping are reached, the weights obtained will be stored and will then be used as weights in the testing phase. This testing phase is to perform the forward propagation phase using input that has never been trained, and utilizing the weights obtained from the training phase earlier.

3. Research Methodology

3.1. Population and Sample

The population in this study is in the form of images or objects of roses. There are 3 types of roses used, namely burgundy roses, osiana roses and damascus roses. As for the sample used in this study amounted to 150 images where each type or class of each 50 images of roses.

The text of your paper should be formatted as follows:

3.1.1. Variables and Variable Operational Definitions

The variables used in this study are shown in Table 4.1 regarding the explanation and operational definition of the research which is an explanation of each variable.

Table 1. Variable Operational Definitions

No	Variable	Code	Variable Operational Definitions
1	Burgundy Roses	'ht(number).jpg	Image of burgundy roses
2	Osiana Roses	'or(number).jpg	Image of osiana roses
3	Damascus Roses	'dr(number).jpg	Image of damascus roses

3.1.2. Types and Sources of Data

The type of data used in this study is secondary data. The data is obtained by crawling the image of puppet characters on the Google search engine using Fatkun Image Downloader. This software is an additional feature of Google Chrome.

3.1.3. Data Analysis Method

Some of the data analysis used in this study are as follows:

- 1) Image histogram, which is used to view the representation of color distribution in an image.
- 2) Deep Learning method, namely Convolutional Neural Network, is used to classify images or images.
- 3) The number of convolutional layers used in this study is 4 layers and the activation function used in this study is ReLU.
- 4) Researchers will conduct several testing scenarios to be able to choose the best model. The predetermined test scenarios are the comparison of the input size, the dropout size on the last layer, the number of neurons in the last layer and the training and testing data partitions.
- 5) In selecting the best model for object (image) classification in the Convolutional Neural Network algorithm, the researcher will choose the best model in terms of accuracy and loss values from the comparison of the test scenarios in point 4 above. The best model chosen is the one with the highest

accuracy value and the smallest loss value.

4. Result of Analysis

4.1. Image Histogram

One of the formats that can be used to display image data is image data with three degrees of color, namely red (red), green (green) and blue (blue) or often referred to as RGB. In this study, the image of the rose to be used is a color image, so there is no need to change the downloaded image. The following is an example of a representation of a rose image obtained using Rstudio software. The use of sections to divide the text of the paper is optional and left as a decision for the author. Where the author wishes to divide the paper into sections the formatting shown in table 2 should be used.



Figure 6. Damascus Roses (HobbyKafe, 2015)

The rose image above has a lot of information contained, including pixel size, image channel and image histogram which can represent the basic formation of the image above. The process of image manipulation can be done with the help of R. software.

```
Image
colorMode      : Color
storage.mode : double
dim
              : 500 500 3
frames.total : 3
frames.render: 1

imageData(object)[1:5,1:6,1]
      [,1] [,2] [,3] [,4] [,5] [,6]
[1,] 0.3764706 0.3725490 0.3647059 0.3529412 0.3372549 0.3176471
[2,] 0.3647059 0.3607843 0.3529412 0.3411765 0.3254902 0.3098039
[3,] 0.3529412 0.3490196 0.3411765 0.3294118 0.3176471 0.3019608
[4,] 0.3450980 0.3411765 0.3333333 0.3254902 0.3137255 0.3019608
[5,] 0.3490196 0.3450980 0.3372549 0.3294118 0.3215686 0.3137255
```

Figure 7. Image Information

The image above includes an RGB color image marked with the meaning of color on the colorMode line. The dimension size of the image above is 500x500 pixels and has an RGB channel of The value or number in the matrix form above describes the brightness level of a color at each pixel of the rose image above, but the value that can be displayed is only up to the fifth line. and the sixth column only because of limitations in displaying output in RStudio.

The representation of the RGB distribution of the Damascus rose image is shown in the following figure. The resulting histogram contains a numeric value of 750000 pixels. This value is obtained from the multiplication of the dimensions of the image size, namely 500 x 500 x 3, which indicates the number of elements or parts that make up the image.

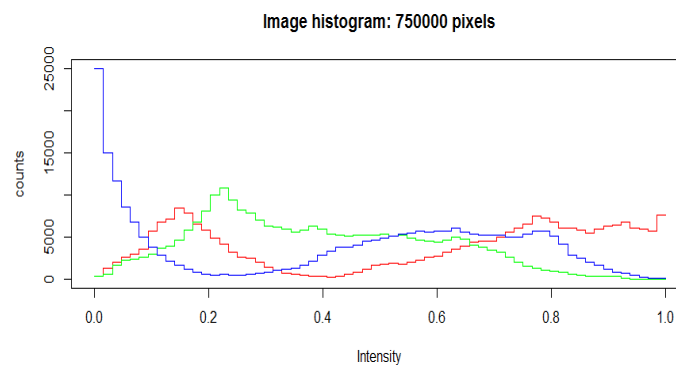


Figure 8. Image Histogram

4.2. Effect of Input Size Scenarios

The image size used can affect the detail of the image on the flower. In general, if you use a larger input image size, the accuracy value of the test data will be higher. In this study, the size of the input image measuring 32 x 32 pixels will be compared with the input image measuring 64 x 64. The results of the input image size comparison scenario are shown in table 4.2 below.

Table 2. Input Size Determination Scenarios

Input Size Scenarios	Data Training Accuracy	Data Testing Accuracy
32 x 32	100%	96,66 %
64 x 64	90,83%	70 %

The experimental results shown in the table above can be seen that data with an input image size of 32 x 32 pixels has a higher accuracy than data with an input image size of 64 x 64 pixels, both for testing and training data. The input size that will be used for the next analysis process is 32 x 32 pixels. Then the dropout value will be compared which will be selected the best for the next analysis process.

4.3. The Effect of the Dropout Scenario on the Last Layer

The overfitting of the model can be overcome by implementing a regularization method such as dropout. The dropout method was used in a study in 2014, this study showed a decrease in the error graph of the two same network structures when subjected to the dropout method (Srivastava, et al., 2014). The use of dropout probability can affect the performance of CNN. Regarding the dropout method, in applying this method there is a probability that must be determined. This probability represents the number of units that will dropout a layer. There is no research that can determine how many probabilities should be used, but the probability values that can be used range from 0 to 1. In this study, the researcher wants to compare several dropout probability values. The results of the comparison scenario using the dropout value are shown in table 4.3.1 below.

Table 3. Dropout Determination Scenarios

Last Dropout Layer Scenarios	Accuracy Data Training : Data Testing	Loss Data Training : Data Testing
0,1 %	72,5% : 73,33%	0,634 : 0,684
0,01%	100% : 96,66%	0,0194 : 0,304
0,001%	100% : 96,66%	0,0011 : 0,0307

Based on the comparison table above, the application of a dropout with a probability of 0.001% has the highest accuracy value and the lowest loss value when compared to the dropout probability values of 0.1% and 0.01%. From this table it can also be seen that the use of the dropout probability value of 0.01% and 0.001% has the same accuracy value in the test data and training data. What distinguishes between the two is the result of the loss value on the test data and training data. The dropout probability value of 0.001% has a loss value that is smaller than the dropout value of 0.01%. The best model of this scenario is to use a dropout probability of 0.001%. The dropout value in the last layer that will be used for the next analysis process is 0.001%. Then the number of neurons in the last layer will be compared which will be selected the best for the next analysis process.

Table 4 Scenario Determination of Neurons Number

Last Dropout Layer Scenarios	Accuracy Data Training : Data Testing	Loss Data Training : Data Testing
125	100% : 96,66%	0,0011 : 0,0307
250	100% : 96,66%	0,0005 : 0,105

The number of neurons that gave the smallest loss value was 125. The number of neurons in this study did not affect the accuracy of the model, but it did affect the loss value in the training and testing data. The best model of this scenario is to use the number of neurons of 125. The number of neuron layers in the last layer that will be used for the next analysis process is 125. Then the scenario of sharing (partitioning) training and testing data will be selected which is the best.

Table 5. Scenario of Total Data Training and Testing

Data Training : Data Testing Scenarios	Count of Data Training : Data Testing	Data Testing Accuracy	Loss Value
60% : 40%	90 : 60	96,66 %	0,0909
70% : 30%	105 : 45	95,55%	0,1629
80% : 20%	120 : 30	96,66 %	0,0307

The best result of this scenario is to use a data training and testing scenario with a ratio of 80%: 20%. When compared with other scenarios, the accuracy of the 80%: 20% data partition has the highest accuracy value and the lowest loss value of the 70%: 30% data partition and 60%: 40%. This happens because the learning process is carried out with more training data, the system will also learn more than other scenarios.

5. The Best Scenario

The best model chosen is the model that has the highest accuracy value for training data and testing data from all scenario testing. The test in the first scenario is to compare the size of the image input between 32 x 32 pixels and 64 x 64 pixels. In this first scenario testing, the selected model is the image input size of 32x32 pixels because it has a higher accuracy value on the test data, namely 96.66% than the image input size of 64x64 pixels, namely 70%. The test in the second scenario is to compare the dropout value in the last layer, which is between 0.1%, 0.01% and 0.001%.

The application of a dropout with a probability of 0.001% has the highest accuracy value and the lowest loss value when compared to the dropout probability value of 0.1% and 0.01%. From this table it can also be seen that the use of the dropout probability value of 0.01% and 0.001% has the same accuracy value in the test data and training data. What distinguishes between the two is the result of the loss value on the test data and training data. The dropout probability value of 0.001% has a loss value that is smaller than the dropout value of 0.01%.

The best model of this scenario is to use a dropout probability of 0.001%. Testing in the third scenario is to compare the number of neurons in the last layer, which is between 125 and 250. The number of neurons giving the smallest loss value is 125. The number of neurons in this study does not affect the accuracy of the model, but affects the loss value in training and testing data. The best model of this scenario is to use the number of neurons of 125. Testing in the last scenario is to compare the distribution of training data and testing data, namely between 60%: 40%, 70%: 30% and 80%: 20%.

The best result of this scenario is to use a data training and testing scenario with a ratio of 80%: 20%. When compared with other scenarios, the accuracy of the 80%: 20% data partition has the highest accuracy value and the lowest loss value of the 70%: 30% data partition and 60%: 40%. The best model chosen is a network using 4 convolution layers, 2 pooling layers, 3x3 kernel size, a softmax layer, a fully connected layer, 32 filters on convolution layers 1 and 2, 64 filters on convolution layers 1 and 2. , the dropout value after the first pooling layer is 0.1%, the dropout value after the second pooling layer is 0.01%, the input size is 32 x 32 pixels, the dropout value on the last layer is 0.001%, the number of neurons in the last layer is 250 and the distribution training and testing data of 80%: 20%.

Table 6. Accuracy Results on Training and Testing Data

Data	Count	Loss	Accuracy
Training	120	0,001126901	100%
Testing	30	0,03076569	96,66%

The plot of the performance results from the loss and accuracy values generated from the model that was formed can be shown in Figure 9 below.

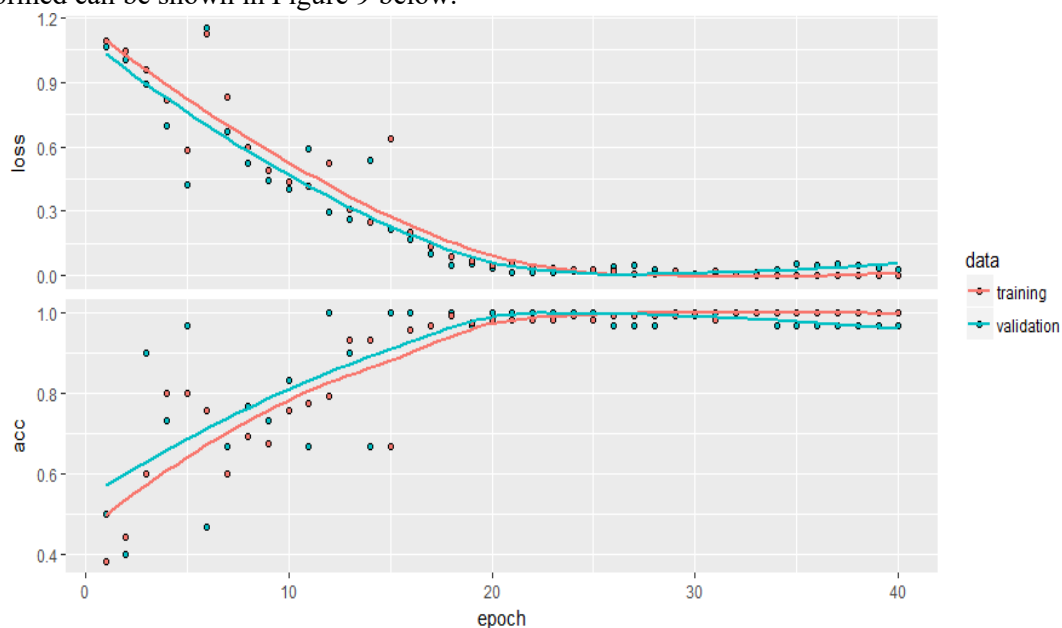


Figure 9. Plots of Accuracy and Loss Value Result

Based on table 5.1, it can be seen that the resulting loss value in the training data is 0.001126901. When compared with the loss value in the testing data, the loss value in the training data is smaller so that this value can be said to be quite low and good from the model obtained. This is supported by the high accuracy value for each data. The training data has an accuracy value of 100% and 96.66% on the testing data. The resulting model can be said to be able to classify well because it has a low loss value and high accuracy value.

The results of the classification on the training data can be shown in the confusion matrix table below.

Table 7. Classification Results on Training Data

	Burgundy	Osiana	Damascus
Burgundy	40	0	0
Osiana	0	40	0
Damascus	0	0	40

From the table above, it can be seen that in the training data all images are classified appropriately by the formed model and there is no error at all in the classification process. This can also be seen from the accuracy value generated in the training data, which is 100%. The classification results of the testing data can be seen in the following table 7 confusion matrix.

Table 8 Classification Results on Training Data

	Burgundy	Osiana	Damascus
Burgundy	10	1	0
Osiana	0	9	0
Damascus	0	0	10

The classification results on the testing data as shown in table 4 can provide an explanation that not all images are classified correctly into their class. This can be seen from the classification results of the Osiana rose. In the table, out of 10 images of the Osiana rose, there are 1 image misclassification.

6. Conclusion

The best model for classifying roses flower is obtained from 32 x 32 pixel images, with the combination of 4 convolution layers, 2 pooling layers, 3x3 kernel size, one softmax layer, and a fully connected layer. This model reached 96.33% in accuracy with RGB images. But the accuracy decreases with 64 x 64 pixel images. Further research should be focused on increasing the accuracy with 64 x 64 pixel images, as this research can only get roughly 70% in accuracy.

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