Classification of Paddy Growth Phase Based on Landsat-8 Image with Convolutional Neural Network Algorithm

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Abstract. Food security is one of the major issues in the world. One of the related component of the issue is the provision of agricultural data. In Indonesia, there is a difference of rice production data between the Ministry of Agriculture and Statistics Indonesia (locally known as BPS). This is due to difference in data acquisition methods used. In order to predict rice production, we must know about paddy growing phase so that the prediction of rice production in a certain period can be accurately calculated. This research aims to propose a convolutional neural network method to develop paddy growth phase classification model using remote sensing data of landsat-8 images. The convolutional neural network algorithm is used to perform self-learning processes such as reading image, extracting and classifying by changing the structure of landsat-8 image into matrix or pixel. This research also conducted experiment against hyper parameter epoch with 10, 30 and 50 epochs to get good accuracy. The case research is the area of PT Sang Hyang Seri rice field in Subang Regency, Indonesia. The experiment results provided an accuracy of 80.37%. It means the convolutional neural network model is matched with the data. It is able to classify landsat-8 images.

1. Introduction
Food security is a major issue that has become the main problem in every country. One of the related components of that issue is the provision of agricultural data. In Indonesia there are two reference of agricultural data, the first one from Minister of Agriculture and the second from Statistics Indonesia (locally known as BPS). The data from those agencies was different. This is due to difference in data acquisition methods used. The Ministry of Agriculture used eyes observation while BPS used the area sample frame method. Both of them used conventional methods. The weakness of such methods is expensive and takes a long time so we need another method to overcome these weaknesses. We must know the paddy growth phase or the classification of paddy growth phases before predict rice production so that the prediction of rice production in a certain period can be calculated accurately.

Nowadays, the development of remote sensing technology is so fast. It makes multispectral image considered capable to solve the problem of determining the paddy growth phase or classification of paddy growth phase. Remote sensing data that can be easily downloaded and accessed is Landsat-8 image. Landsat-8 image was launched in 2013 and until now has recorded almost the entire region on earth continuously [4]. Landsat-8 image is a satellite with a wide area and has a spatial resolution of 30 m which can be used for studies at a regional scale, equivalent to a district area. The technology that utilizes Landsat-8 image has begun to be applied in various fields, including for weather forecasting, crop forecasting, mineral resource research and other applied fields.
In the current era of industrial revolution 4.0, a method that developed to classify data automatically is deep learning. The deep learning method can learn several hierarchical feature layers and turn it into input data, so the segmentation process on Landsat-8 image is carried out automatically. The deep learning will create multilayer network of artificial neurons to classify input data and produce output data. The deep learning’s algorithm that used in this research is Convolutional Neural Network (CNN). CNN algorithm is capable of self-learning process for object recognition, object extraction and classification and also can be applied to high-resolution images that has nonparametric distribution model [9]. The research was compared the method between CNN and Support Vector Machine (SVM) for classification of paddy growth phase. The result showed CNN was better than SVM to classify paddy growth phase [7]. Based on this, this study aims to classify paddy growth phase based on Landsat-8 image with convolutional neural network algorithm in the paddy area of PT. Sang Hyang Seri Subang Regency.

2. Methodology

2.1. Convolutional Neural Network

Convolutional Neural Network (CNN) is one of the algorithms from deep learning methods that has a high neural network depth and applied to process data in two-dimensional form, such as images [3]. CNN is used to classify labeled data using supervised learning methods. The architecture CNN consists of feature extraction layer (convolution layer and pooling layer) and classification layer (fully-connected layer).

In convolution layer, there is a convolution operation. Convolution operation is the multiplication between input data and kernel. Kernel is a weight parameter in array multidimensional form. These weight values are obtained using an initializer determination that available in the MXNet library. In image processing, the way convolution operates is to move a kernel $W$ with $m \times n$ on image $I$ with $i \times j$.

Convolution operation is defined as an equation 1 [5].

$$s[i, j] = (I \ast W)[i, j] = \sum_{m} \sum_{n} I[i + m, j + n]W[m, n]$$  \hspace{1cm} (1)

Where:

$I \ast W)(i, j)$ = result function of convolution operation
$I$ = input matrix
$W$ = kernel matrix
$m, n$ = kernel size number

After convolution operations, data will be processed on pooling layer. Pooling operations are carried out by reducing size of matrix (example max-pooling or average pooling). Output from pooling layer operation is a matrix with smaller dimensions compared to the initial image. Convolution and pooling process is carried out to obtain the desired feature map to be input into fully-connected layer [3]. Fully-connected layer is a layer where all neurons from the previous layer are connected to neurons in the next layer as well as an ordinary artificial neural network. The matrix from the previous layer needs to be converted into one dimensional data, that called vectors. In this layer will be determined which features are most correlated with a particular class [2]. The equation of the fully-connected layer process is as follows:

$$\hat{y} = w_0 + \sum_{i=1}^{n} x_i w_{ik}, \hspace{0.5cm} k = 0,1,2,...,t$$ \hspace{1cm} (2)

Where:

$\hat{y}$ = fully connected layer output
$w_0$ = bias
$n$ = the number of data on each unit
$x_i$ = input value
$w$ = weight
$t$ = the number of target on fully connected layer
2.2. The Data
The data used in this study are Landsat-8 image from November 2015 - March 2017 rice field area of PT. Sang Hyang Seri in Subang Regency. There are three phases in the research that are used as data classes sequentially, namely the vegetative phase (1-60 days), the generative phase (61-90 days) and the ripening phase (91-120 days). Landsat-8 period in every 16 days. Also, realization of rice planting data at PT. Sang Hyang Seri Subang Regency from November 2015 - March 2017 which was researched by PUSFATJA LAPAN. Another supporting data is shape file of PT. Sang Hyang Seri Subang Regency. Here is a breakdown of the amount of data for each class:

| Code | Class            | Amount |
|------|------------------|--------|
| 1    | Vegetative Phase | 307    |
| 2    | Generative Phase | 110    |
| 3    | Ripening Phase   | 430    |

2.3. Data Analysis
Data analysis in this study used Toshiba laptop processor intel core i5 CPU 64-bit RAM 2 GB. The software used for data processing is RStudio with the package rgdal, gdalUtils, raster for image cutting, abind, MXNet for modeling and confusion matrix for model evaluation. The steps of the analysis are as follows:
1. Download Landsat-8 image from November 2015 – March 2017 rice fields area of PT. Sang Hyang Seri Subang Regency via Google Earth Engine (GEE) with data corrected geometric and radiometric, namely LC08/C01/T1_SR. Each Landsat-8 image consists of 1 – 7 bands.
2. Clipping Landsat-8 image according to rice fields blocks using SHP map. Rice fields area of PT. Sang Hyang Seri consists of 194 blocks. The purpose of clipping Landsat-8 image to get data each block according to the age.
3. Perform data fairness checks to remove NA data due to cloud cover.
4. Change the image size to 32x32 pixels to make computing process faster. If we use an original image, image processing will take a long time. Resizing an image does not remove information from the image.
5. Split data into training data and testing data with proportion of 80:20. Train the convolutional neural network model using train data and then evaluate using test data.
6. Perform model experiments using epoch to improve model accuracy.
7. Evaluate the classification model of the experimental result with accuracy, sensitivity and specificity values using confusion matrix.

\[
\text{Accuracy} = \frac{TP_A + TP_B + TP_C}{(TP_A + TP_B + TP_C) + \sum_{A \neq A} E_{ij}} \quad (3)
\]

\[
\text{Sensitivity}_A = \frac{TP_A}{TP_A + FN_A} \quad (4)
\]

where \( FN_A = E_{AB} + E_{AC} \)

\[
\text{Specificity}_A = \frac{TN_A}{FP_A + TN_A} \quad (5)
\]

where \( FP_A = E_{BA} + E_{CA} \)

\( TN_A = (TP_B + TP_C) + E_{BC} + E_{CB} \)

- TP\(_A\): True positive, is a condition where the correct predicted value predicts class A.
- TN\(_A\): True negative, is a condition where the correct predicted value predicts class outside A.
- FP\(_A\): False positive, is a condition where the model predicts class A but actually class outside A.
- FN\(_A\): False negative, is a condition where the model predicts class outside A but actually class A.
3. Result and Discussion

3.1. Landsat-8 Image in Rice Field Area

PT. Sang Hyang Seri is state-owned enterprise engaged in agriculture, such as the provision of production facilities, processing of agricultural products as well as research and mining. This research is located in the working area of PT. Sang Hyang Seri, Sukamandi, Subang Regency. In remote sensing data such as Landsat-8, one of the main challenges is atmospheric disturbances in the form of clouds and hazes. Cloud interference (cloud cover and its shadow) cannot be fixed in general. This interference is represented as missing data. Subang regency is a cloudy area. If the area where the cloud cover is removed then quite a lot of Landsat-8 image is lost each period. The cloud cover is at different coordinate points. Figure 1 is an example of the display of Landsat-8 in the rice fields of PT. Sang Hyang Seri Subang Regency. This image is cleared, it can be seen the boundary lines between blocks.

![Figure 1. Landsat-8 period August 1st, 2016](image)

3.2. Accuracy and Misclassification

The research was conducted by giving a deeper convolution layer and doing preprocessing method and adding stride. In this study, used 2 layers convolution and pooling layer with filter 3×3 and stride 2×2 for first convolution and pooling layer. In second layer used filter 2×2 and stride 2×2. Also 2 fully connected layer with dropout probability value 0.1 and SoftMax function. The classification process is done after image becomes a dataset that is ready to be trained. The dataset is divided with ration of 80% training data and 20% testing data.

This study used epoch for experiment of hyper parameter. Epoch is the number of iteration that models do to train data. The epoch value that is too small can cause underfitting model, but the high epoch can cause overfitting model. Experiments are needed to get optimal epoch values. This experiment was conducted in 3 steps. The first step is carried out using 10 epochs, the second step used 30 epoch and the last one used 50 epochs. Here is a comparison of confusion matrix between those steps:
Table 2. Confusion matrix of the experiment hyper parameter epoch

| Epoch | Predict | Actual | Accuracy (%) |
|-------|---------|--------|--------------|
|       | 1       | 2      | 3            |
| 10    | 1       | 40     | 5            | 6            | 64.48% |
|       | 2       | 17     | 10           | 4            |          |
| 30    | 1       | 48     | 4            | 2            |          |
|       | 2       | 10     | 14           | 6            | 72.89%  |
| 50    | 1       | 51     | 4            | 0            |          |
|       | 3       | 3      | 16           | 5            | 80.37%  |

Based on table 2, if used 10 epochs, the accuracy data is 64.48%. Misclassification occurs between classes. From 107 test data, 65 were correctly classified and 42 were incorrectly classified. In vegetative class, 61 sample test data, only 40 data were correctly classified. 17 data were incorrectly classified into generative class and 4 data into ripening class. Also misclassification occurs between generative and ripening class. If used 10 epochs, the accuracy data is 72.89% but also misclassification occurs between classes. From 107 test data, 78 were correctly classified and 29 were incorrectly classified. In generative class, 22 sample test data, 14 data were correctly classified. 4 data were incorrectly classified into vegetative class and 4 data into ripening class. The result from the last experiment provided an accuracy of 80.37. From 107 test data, 86 were correctly classified and 21 were incorrectly classified. In ripening class, 24 sample test data, 19 data were correctly classified and 5 data were incorrectly classified into generative class.

It can be concluded that by using epoch as many as 50 will get the highest accuracy. It means a potential model to be developed as information to classify paddy growth phase. The classification accuracy increases when the epoch changes into large value. Based on table 2, we can be obtained sensitivity and specificity value as follows:

Table 3. Sensitivity and specificity value

| Class | Sensitivity (%) | Specificity (%) |
|-------|----------------|-----------------|
| 1     | 83.16          | 91.30           |
| 2     | 72.72          | 90.59           |
| 3     | 79.16          | 89.16           |

Based on table 2 and 3, we can conclude that the accuracy of 80.37%, sensitivity of 78.50% and specificity of 90.35% was balanced. It means the better classification prediction results. It means the convolutional neural network model is matches with the data and able to classify landsat-8 images.

4. Conclusion
In this study, experiments were conducted on the value of epoch hyper parameter. The classification accuracy increases when the epoch changes into large value. The best accuracy is 80.37% for 50 epochs with sensitivity of 78.60% and specificity of 90.75%. The result presented in this study that convolutional neural network algorithm is able to classify data into a model that can be solution for predict rice production data.

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