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Sentinel-1A image classification for identification of garlic plants using decision tree and convolutional neural network

Risa Intan Komaraasih, Imas Sukaesih Sitanggang, Annisa, Muhammad Asyhar Agmalaro
Department of Computer Science, Faculty of Mathematics and Natural Sciences, IPB University, Bogor, Indonesia

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ABSTRACT

The Indonesian government launched a garlic self-sufficiency program by 2033 to reduce imports by monitoring garlic lands in several central garlic areas. Remote sensing using satellite imageries can assist the monitoring program by mapping the garlic lands. A previous study has classified Sentinel-1A satellite imageries to identify garlic lands in Sembalun Lombok Indonesia using the decision tree C5.0 algorithm with three scenarios data input and produced a model with an accuracy of 78.45% using scenarios with two attributes vertical-vertical (VV) and vertical-horizontal (VH) bands. Therefore, this study aims to improve the accuracy of the classification model from the previous study. This study applied two classification algorithms, decision tree C5.0 and convolutional neural network (CNN), with two new scenarios which used two new combinations of attributes). The results show that the use of new data scenarios as input for C5.0 can not increase the previous model's accuracy. While the use of the CNN algorithm shows that it can improve the previous study's accuracy by 7.91% because it produced a model with an accuracy of 86.36%. This study is expected to help garlic land identification in the Sembalun area to support government programs in monitoring garlic lands.

Corresponding Author:

Annisa
Department of Computer Science, Faculty of Mathematics and Natural Sciences, IPB University
Raya Dramaga Road, IPB University, Dramaga, Bogor 16680, West Java, Indonesia
Email: annisa@apps.ipb.ac.id

1. INTRODUCTION

Garlic belongs to the vegetable group with the Latin names Allium sativum L [1]. It is one of the popular agricultural commodities in Indonesia due to high domestic demand. Every year there is an increase in garlic consumption, but it is not followed by increase in domestic garlic production. As result, Indonesia imports 95% of total domestic needs [2], [3]. To reduce this number, the government has implemented several garlic self-sufficiency programs, namely expanding garlic cultivation areas, self-help farmers, and the obligation of importers to plant garlic in several garlic centers. The government supervises the program by implementing a monitoring system by a verification team appointed by the Director-General of Horticulture, Ministry of Agriculture Indonesia. The use of remote sensing can assist the government in monitoring by obtaining a map of the location of garlic plantations faster and more efficiently [4]. The remote sensing data used is Sentinel-1A satellite imagery which allows land cover mapping to have a high spatial and temporal resolution of 10×10 m and comprehensive area coverage.

Nurkholis *et al.* [5] have made a model of garlic land suitability using spatial decision trees to assist the government in evaluating the suitability of garlic land so that domestic garlic production can increase. The study uses a spatial dataset consisting of a target layer representing the suitability of garlic land and ten explanatory layers representing land and weather characteristics in the study area of Magetan and Solok, Indonesia. The results produced a model with high accuracy of 94.34% [5]. As in [5], many previous studies have used Sentinel-1A images to classify land cover [4]–[9]. Deepthi *et al.* [6], a study was conducted to classify Sentinel-1A into two classes, namely urban and non-urban, using the Sentinel-1 statistical analysis of dual polarization data and turn it into an interpretation graph, the result is a classification model with reasonably low accuracy, around 68-71%. Furthermore, a study compared several types of algorithms for processing Sentinel-1A images, and the results showed that support vector machine (SVM) got the best accuracy from using dual date Sentinel-1A images (in December and January 2019) to classify land cover into six classes [7]. The model's accuracy obtained using the SVM algorithm is 74.4%, followed by the decision tree algorithm, which produces an accuracy of 69.7%. A study classified land cover into five classes using Sentinel-1A with the SVM algorithm [8], [9]. This study uses the vertical-vertical (VV) and vertical-horizontal (VH) bands owned by Sentinel-1A and the combination of these attributes, namely VV/VH, VV-VH, and (VV+VH)/2. This study applies eight data scenarios as input data. The best classification model has an accuracy of 93.28% using three attributes, namely VV, VH, and VV-VH [8]. The results of this study also emphasize the importance of using different attributes in image classification because it can increase the accuracy of the models. Deep learning was applied to classify Sentinel-1A images [10]. The study compared the use of two different algorithms, namely machine learning (random forest (RF)) and deep learning (convolutional neural network (CNN)). The use of Sentinel-1 proves that the CNN algorithm increased the accuracy generated by the RF algorithm up to 3%, and the highest accuracy reached 94.1% [10].

The use of Sentinel-1A imagery to identify garlic plantations has also been carried out [11], [12]. Tian *et al.* [11] stated that Sentinel-1A is capable of characterizing the growth cycle of summer maize irrespective of weather conditions. Sentinel-1A images were classified to identify garlic and non-garlic plantations using the decision tree C5.0 algorithm [12]. The study used VV, VH, and their combinations, namely VV-VH, VV/VH, and (VV+VH)/2. Two scenarios were adopted from [8], which produces the two highest accuracies, namely the 7th (using three attributes namely VV, VH and VV-VH) and 8th (using five attributes namely VV, VH, VV-VH, VV/VH, (VV+VH)/2) scenarios as input data. However, the best model still has a relatively low accuracy of 78.45% using only two attributes, namely VV and VH. Therefore, this study aims to improve the accuracy of the garlic land classification model in [12] by applying the decision tree C5.0 algorithm [13] and CNN [14] on Sentinel-1A imageries of Sembalun. Sembalun is one of the garlic cultivation centers in District East Lombok Indonesia. The results of this study are expected to support government program in the monitoring system of the garlic field. The contribution of this study is a classification model to identify garlic land using the CNN algorithm that has a better performance compared to the decision tree-based model proposed in the previous study [8]. Based on the result, we find that the CNN algorithm is potential to be used in analyzing satellite images including Sentinel-1A in the application of precision agriculture.

2. ALGORITHMS

2.1. Decision tree C5.0

The concept of a decision tree is to convert data into a decision tree and decision rules [13]. Decision trees are one of the most popular classification methods because they are easy to be interpreted by humans. The C5.0 algorithm is one of the decision tree algorithms, a refinement of the iterative dichotomiser 3 (ID3) and C4.5 algorithms. C5.0 is better than C4.5 in terms of speed, memory usage efficiency, decision tree size, and misclassification [15]. C5.0 can also handle continuous and discrete attributes, and C5.0 decision tree results can be pruned or not pruned. In the C5.0 decision tree algorithm, the selection of attributes uses information gain. In the C5.0 algorithm, the size of the attribute selection uses information gain and entropy. Entropy is a parameter to measure the diversity of a data set-the more heterogeneous the dataset, the greater the entropy value. Information gain (Gain(A)) is a measure of the effectiveness of an attribute A in classifying data whose highest gain value is chosen as the "solve" attribute on the node [16]. The formula of the entropy and gain value are defined in (1), (2), and (3) [16].

$$Entropy(D) = -\sum_i^m p_i log_2 p_i \tag{1}$$

$$Entropy_A(D) = \sum_j^v \frac{|D_j|}{|D|} \times Entropy(D_j) \tag{2}$$

$$Gain(A) = Entropy(D) - Entropy_A(D) \tag{3}$$

Where m is class, p_i is the proportion of the samples that belong to class m for a particular node, v is feature split on, $|D_j|$ is the j-th child node's, D is the parent node's dataset.

2.2. Convolutional neural network

CNN is the multilayer perceptron (MLP) development and one of the most popular algorithms used for deep learning. On CNN, each neuron is presented in 2-dimensional form, so this method is suitable for processing with image input [14]. CNN works hierarchically. The CNN structure consists of input, feature extraction, classification, and output, as described in [17]. The feature learning stage is object extraction from the input image. The deeper the image, the more extractions are obtained so that the patterns obtained are also more clearly formed [18]. Feature learning consists of two layers: the convolutional layer and pooling layer [19].

In contrast, the classification process consists of fully connected and activation functions (sigmoid) whose output is a classification result [20]. The convolution layer uses a filter containing weights to extract objects such as edges, curves, or colors from the input image. Some parameters can be changed to modify the treatment of each layer, namely filter size, stride, and padding. Stride controls how the filter moves on the input data. Padding is the increase in pixel size around the input data. Rectified linear unit (ReLU) is one of the activation functions used to eliminate negative values in the image. Pooling (subsampling) is a reduction in the size of the matrix. The fully connected layer connects all nodes into one dimension [21]. The sigmoid activation function is used to obtain the classification results. The activation function provides rules/guards for neurons so that the probability value of the final result is between 0 and 1 [22].

3. RESEARCH METHOD

3.1. Dataset

The data used in this study is Sentinel-1A satellite imageries data that have been pre-processed in the study area, which is around the slopes of Mount Rinjani, Sembalun District Lombok, Indonesia. It was obtained from the study of [12]. There are four Sentinel-1A images acquired on 13th and 25th July and 10th and 22nd November 2019. Detailed characteristics of the data used are shown in Table 1. The time difference between the acquisition dates was based on garlic planting time in the study area, obtained from garlic farmers in the area. According to garlic farmers in the study area, garlic was planted in July 2019 then harvested in November 2019, with only a few areas not being harvested. This information is used to label garlic and non-garlic classes on images.

Table 1. Specifications of Sentinel-1A images [12]

Specifications	Sentinel-1A experiment data
Acquisition time	13/07/2019; 25/07/2019; 10/11/2019; 22/11/2019
Acquisition orbit	Ascending
Imaging Mode	IW (Interferometry Wide Mode)
Image frequency	C-band (5.46 Hz)
Polarization	Dual polarization (VV-VH)
Data product	Level-1 GRD (Ground Range Detected)
Resolution mode	10×10 m

The four images were converted into two datasets, namely dataset A and dataset B, with sampling for each class in the two datasets are shown in Table 2. Sampling and data labeling were carried out on images on July 13th and 25th, 2019, for the garlic class, while the dates 10th and 22nd November 2019 for non-garlic classes. Sampling was done by selecting sites on the Sentinel image and comparing it with the image on Google Satellite to ensure that each site chosen has the correct class. There are two types of data used in this study: image data and data extracted from the image in tabular data. There are two main attributes from the image extraction, namely VV and VH, as described in Table 3. Image data were used as input from the CNN algorithm, while the Decision Tree was implemented on tabular data.

Table 2. Dataset description for classification in the study [12]

Dataset	Pixel sample for garlic	Pixel sample for non-garlic
A	Pixel collected from the image on July 13th, 2019	Pixel collected from the image on November 10th, 2019
B	Pixel collected from the image on July 25th, 2019	Pixel collected from the image on November 22th, 2019

Table 3. Attributes of image data in the study [12]

Attribute Name	Explanation
VV	The ratio of Vertical beam sensor, Vertical backscatter from the object
VH	The ratio of Vertical beam sensor, Vertical backscatter from the object

3.2. Research stages

The research stages can be seen in Figure 1. This stage consists of several steps, namely data collection, data pre-processing, data partition, classification models creation using the decision tree and CNN algorithms, model evaluation, and visualization of each algorithm's best model classification results. This study also uses additional information to make new bands/attributes derived from existing bands (VV and VH) using several arithmetic formulas.

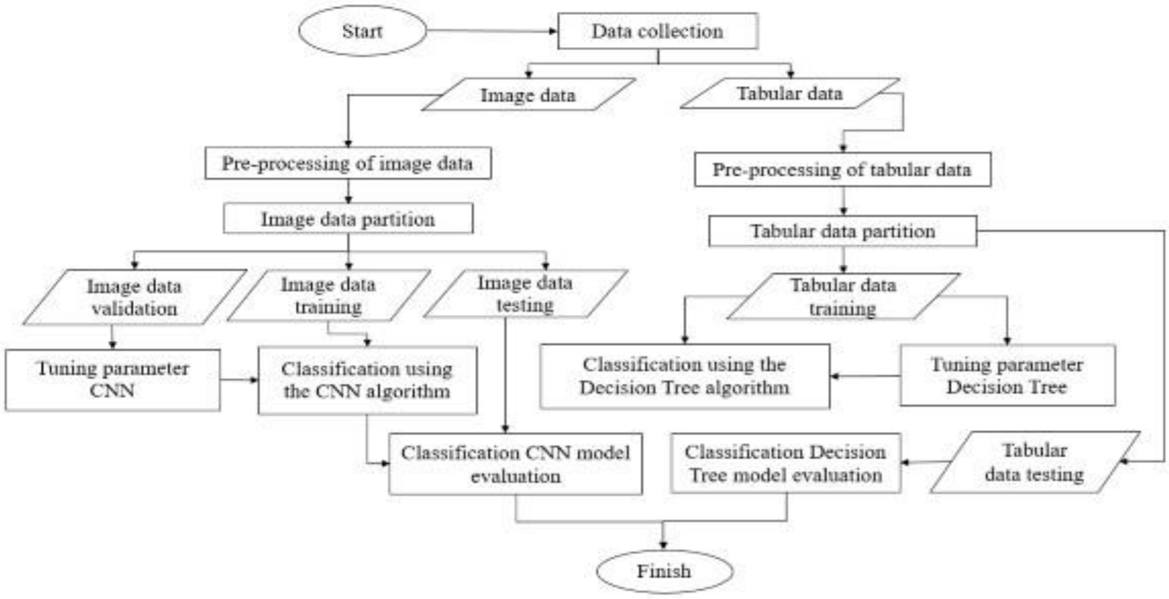

Figure 1. Research stages

3.2.1. Data pre-processing

There are three synthetic bands with the formula: VV/VH, VV-VH, and (VV+VH)/2. Then this synthetic band is combined with the two main attributes so that it becomes several data scenarios, as shown in Table 3. Scenario 1 uses two bands/attributes that are owned by the Sentinel-1A image. Scenarios 2, 3, and 4 are possible compositions to create a red, green, blue (RGB) composite Sentinel-1A image. Data scenarios is needed to increase the model accuracy and determine the combination of bands/attributes that affect classifying garlic planting fields. The study by [12] has used tabular data with data scenarios 1, 2, and 5 in the decision tree C5.0 algorithm. So, the pre-processing stage of tabular data in this study is to create scenarios 3 and 4 as input data to the decision tree algorithm. As for the use of image data, it is necessary to go through several pre-processing stages. This pre-processing consists of creating an image for each scenario whose band values are adjusted to Table 4. The next step is cropping the image according to the input size on CNN and sampling the data, and the final step is grouping the image data into each class.

Table 4. Data scenarios for classifying Sentinel-1A images

Scenario	Number of band/attributes	Description of band/attribute
1	2	VV, VH
2	3	VV, VH, VV-VH
3	3	VV, VH, (VV+VH)/2
4	3	VV, VH, VV/VH
5	5	VV, VH, (VV-VH), (VV/VH), (VV+VH)/2

3.2.2. Data partition

Data partition was done in two types of the data format: images (raster) and tabular (spreadsheet). First, the partition of tabular data uses the 10-fold cross-validation method to improve the accuracy obtained by the model and evaluate the model. The choice of K=10 resulted in a better and more stable estimate compared to other K values [23]. The data partition uses a package from Sickit-learn, namely

StratifiedKFold, with a ratio of 90% training data and 10% test data, so that from 8,400 pixels, 7,560 pixels are taken as training data and 840 pixels as test data for each scenario.

Second, the image data was partitioned into 70% training data, 20% test data, and 10% validation data. The results are 236 images as training data, 34 as validation data, and 66 as test data. The training data is used to train the CNN model. Validation data is used for the model validation process and to determine CNN parameters, usually called hyperparameter tuning. Last, testing data is used to calculate the accuracy of the model.

3.2.3. Classification using decision tree algorithm

The C5.0 algorithm was applied to the dataset with two scenarios, scenario 3 and 4 as shown in Table 4. The tuning parameter was carried out using a grid search to obtain optimal parameter values on decision tree C5.0, resulting in high accuracy models. The parameters to be tuned are max_depth, which is the maximum depth of the tree; max_leaf_nodes are the maximum number of leaf nodes, min_samples_split is the minimum number of samples required to split an internal node, and min_samples_leaf is the minimum number of samples required to be at a leaf node.

3.2.4. Classification using CNN algorithm

The CNN network architecture used in this study is structured as:

- Input size of 5×5 is equivalent to 50 m×50 m
- Two convulsion layers: 50 filters with 3×3 kernel size, ReLU activation function, 50% dropouts, and batch normalization
- Flattening layer, change the output dimension into a one-dimensional vector
- Two fully connected layers: 100 neurons, ReLU activation function 50% dropouts, and batch normalization
- Output layer: number of neurons according to the number of data classes, using the sigmoid activation function.

Tuning parameters using a grid search was also done on the parameters that affect the CNN algorithm during the training process, namely the number of epochs, batch size, and momentum.

3.2.5. Classification model evaluation

The best models of the two algorithms were evaluated using the several metrics derived from the confusion matrix. The confusion matrix has four variables, namely true positive (TP), true negative (TN), false positive (FP), and false negative (FN) [24]. Evaluation metrics used are accuracy, precision, and recall, each formulated in (4), (5), and (6) [25]. In addition, this study evaluates the algorithms based on run time during the model training phase.

This study calculates loss function (cross-entropy loss) in the CNN algorithm implementation. Loss function is a function that measures the model's performance in predicting the target. The Loss Function calculation formula can be seen in (7) [26].

$$Overall\ Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \times 100\% \tag{4}$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \times 100\% \tag{5}$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \times 100\% \tag{6}$$

$$\mathrm{H(p,q)} = -\sum_{\mathrm{i}}^{\mathrm{N}} \mathrm{p_i} \log \mathrm{q_i} \tag{7}$$

Where N is the number of classes, H is cross-entropy loss, p_i is the ground truth probability of the i-th outcome, q_i is the model-predicted probability of the i-th from softmax activation function.

4. RESULTS AND DISCUSSION

4.1. Data

The pre-processing tabular data for each scenario has 8,400 instances (4,200 garlic classes and 4,200 non-garlic classes). Image data pre-processing produces 20 new images, each of which contains approximately 84,000 pixels. If the image is cut into a 5×5 pixel, the results are 3,360 small images. Therefore, the cropping and sampling stages were carried out for each scenario consisting of 10% of the total small-sized images, namely 336 images per 1 scenario (168 images of garlic class and 168 images of non-garlic class).

4.2. Decision tree model classification

This training data learning process uses the decisiontree classifier module, available in the Sickit-learn package in Python. Parameter tuning was done with the GridsearchCV module, in the Sickit-learn package, with a CV (cross-validation) of 5. The accuracy of all folds in scenarios 3 and 4 for each dataset can be seen in Figure 2.

It can be seen in Figure 2 that the use of dataset B is better than the use of dataset A. Almost all of the accuracy results in each scenario in dataset B are higher than dataset A. For example, the highest accuracy using datasets A is 76.43% in scenario 3 and 75.48% in scenario 4. As for dataset B, the highest accuracy is 77.50% in scenario 3 and 78.33% in scenario 4. Thus, the model with the highest accuracy from the decision tree algorithm is obtained on the end-of-month data (dataset B) using three attributes, namely VV, VH, and VV/VH. However, the best model from this algorithm has not been able to produce better accuracy than the model resulted by the study [12].

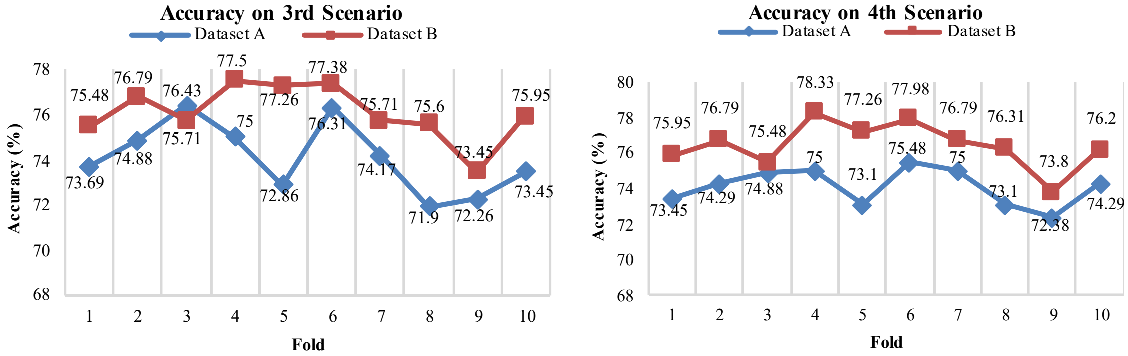

Figure 2. Accuracy of classification models in dataset A and dataset B using decision tree algorithm

4.3. CNN model classification

The model training process uses the Conv2D module, available in the Keras package in Python. The parameters to be tuned are the number of epochs, batch_size, and momentum. The learning rate parameter in this study uses the scheduler provided by the Keras package with an initial value of 0.001. Figure 3 shows that the use of dataset B in Sentinel image classification for garlic is better than the use of dataset A and it is similar to the results of the decision tree model. The highest accuracy of the model on dataset A is 83.33% in scenario 4. Meanwhile, classification on dataset B produces an accuracy of 86.36% in scenario 3. It can be seen that the model which produces the highest accuracy from the CNN algorithm is also obtained from the end-of-month dataset but with different attributes, namely VV, VH, and (VV+VH)/2. As a result, the model can produce an accuracy of 7.91% higher when it is compared to the results of the study [8]. In addition to the accuracy, the running time also influences the selection of the best model. Figure 4 shows that the running times of the two algorithms are quite different when compared. The Decision Tree algorithm is 10% faster than the CNN algorithm, while the difference in accuracy produced is quite different. Thus, the best model is determined using the highest accuracy.

4.4. Classification model evaluation

In this part, we discussed the decision tree implementation on Sentinel-1A. Feature importance is obtained based on the percentage appearance of the attributes of each classification model as shown in Table 5. For example, in dataset A, the most important attribute in scenario 3 is (VV+VH)/2, whereas in scenario 4 is VV. The most important attribute in both scenarios in dataset B is the VH. The study [8] shows that in scenarios 1, 2, and 5, the most important attributes are (VV+VH)/2 and VV. This study also adds the VH attribute because it contributes to the high accuracy of the model on dataset B. Therefore, it can be concluded that the attributes that have the most influence on the garlic and non-garlic land classification model are (VV+VH)/2, VV, and VH.

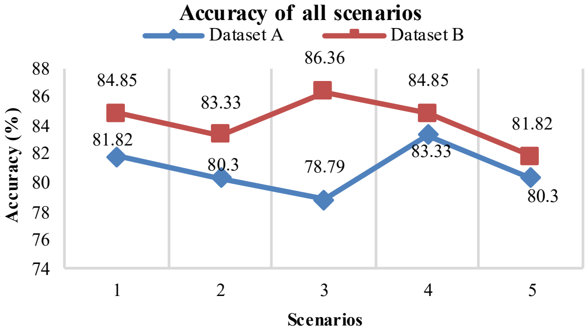

Figure 3. Accuracy of models in dataset A and dataset B using CNN algorithm

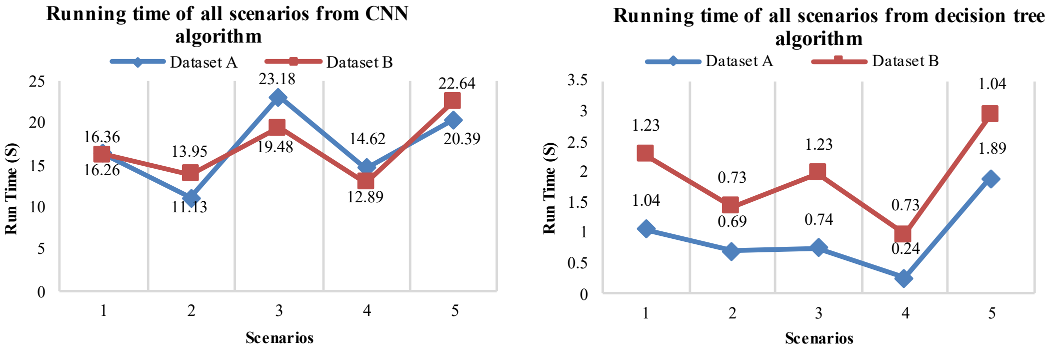

Figure 4. Running time of models in dataset A and dataset B using the CNN algorithm (left) and decision tree algorithm (right)

Table 5. Feature importance of all attributes in each scenario

	Dataset A		Dataset B	
	Scenario 3	Scenario 4	Scenario 3	Scenario 4
(VV+VH)/2	90 %	-	10%	-
VV	7 %	91 %	13 %	18 %
VH	2 %	8 %	77 %	82 %
VV/VH	-	1 %	-	0.2 %

The evaluation was carried out on the best model of the two algorithms. The confusion matrix of the model from the decision tree is shown in Table 6. The precision and recall values of the model is presented in Table 7. This result shows that the best decision tree model can recognize the class of garlic because it has a high recall value of 90% compared to the non-garlic class. However, the model is better to predict the non-garlic class than the garlic class because of the high precision value of 87%.

Table 6. Confusion matrix of the classification model using decision tree

Actual class	Prediction class	
	Garlic	Non-garlic
Garlic	376	44
Non-garlic	138	282

Table 7. Precision and recall of the classification model using decision tree

	Precision (%)	Recall (%)
Garlic	73	90
Non-garlic	87	67
Average	80	78

The confusion matrix of the model from the CNN algorithm can be seen in Table 8. The precision and recall values of the model is presented in Table 9. This result shows that the best model of the CNN algorithm also has the same characteristics as the decision tree model results, which can recognize the garlic class better than the non-garlic class because it has a high recall value of 100%. The model is better to predict the non-garlic class than the garlic class because of the high precision value of 100%. However, when it is compared to the decision tree model, the CNN model produces higher precision and recall values. These results show that the CNN model is better than the decision tree, not only because of the higher accuracy but also because of the better precision and recall values. Furthermore, the best model of CNN is also proven to increase the accuracy of the garlic classification model compared to the model proposed by [12].

Table 8. Confusion matrix of classification model using CNN

Actual class	Prediction class	
	Garlic	Non-garlic
Garlic	33	0
Non-garlic	1	24

Table 9. Precision and recall of the classification model using CNN

	Precision (%)	Recall (%)
Garlic	79	100
Non-garlic	100	73
Average	89	86

The characteristics of the sample data used for modeling were checked, and it was found that the sample data of the five attributes show the same pattern in both classes. The pattern shows that the garlic class's band value range falls into the non-garlic class range as shown in Figure 5. It makes the model difficult to distinguish between the two classes. As a result, the actual location of garlic may be incorrectly classified as non-garlic and otherwise. This result also explains why the accuracy of the model produced in this study is still relatively low.

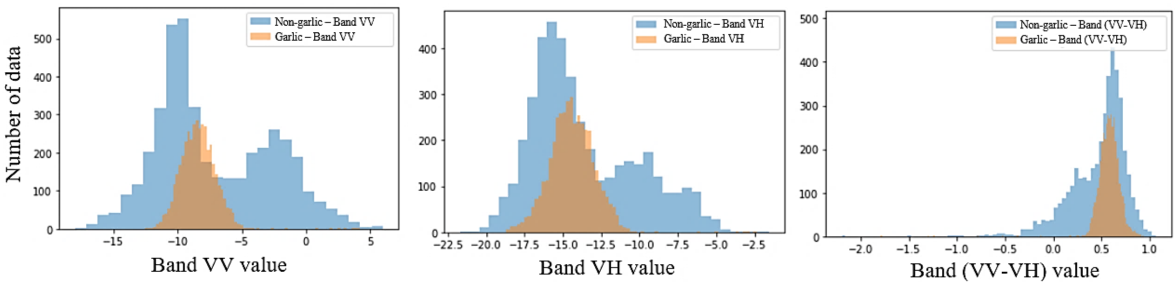

Figure 5. Histograms of the two classes in the VV, VH and (VV-VH) bands of Sentinel-1A images

5. CONCLUSION

This study has successfully implemented decision tree and CNN algorithms on Sentinel-1A image classification in the study areas Sembalun district, Indonesia. The result is the two best classification models for garlic plantation land identification using the decision tree and CNN algorithm. The use of the CNN algorithm produces the best model with an accuracy of 86.36%. These results were obtained using data from the end of July and November 2019. The model was able to predict the data into garlic and non-garlic classes well and was also able to recognize the two classes well. The results also show that the most important band combinations of Sentinel-1A used in garlic identification are VV, VH, (VV+VH)/2 and the use of data at the end of the month is better than the use of data at the beginning of the month because it can produce higher accuracy in each scenario. Because this research only uses information from the satellite imagery (Sentinel-1A satellite band only), which provides limited information/data for making the model classification. Future works are expected: (1) Integrate other information about the growth of garlic to enrich the data used to make models of land classification of garlic and non-garlic plantation lands. (2) Adding the temporal information while acquiring the Sentinel-1A so that the data used can represent the age of the garlic plant.

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BIOGRAPHIES OF AUTHORS

Risa Intan Komaraasih is a Magister student of Computer Science in IPB University, Indonesia. Her research areas are focused on the development of computer science (artificial intelligence, data mining, and expert system) in agriculture, specifically related to Geographical Information System. She can be contacted at email: intan23_risa@apps.ipb.ac.id.

Imas Sukaesih Sitanggang is a Professor of Computer Science in IPB University, Indonesia. Her research interest is spatial data mining and smart agriculture. Her current research project is the development of INA Agro-GARLIC (Agroecological Assessment of Land Suitability for Garlic). She can be contacted at email: imas.sitanggang@apps.ipb.ac.id.

Annisa is a senior lecturer in the Department of Computer Science at IPB University. Her research interests include data mining, skyline query, and recommender system. Her current research focusing on data mining and application of skyline query for recommender system in various fields. She can be contacted at email: annisa@apps.ipb.ac.id.

Muhammad Ashyar Agmalaro is a Lecturer of Computer Science in IPB University, Indonesia. His research areas are focused on the development of computer science (artificial intelligence, data mining, and expert system) in agriculture. He can be contacted at email: agmalaro@apps.ipb.ac.id.