Rice Farming Age Detection Use Drone Based on SVM Histogram Image Classification

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Abstract— Rice is the largest main food commodity in Indonesia. This makes rice farming technology needs to be developed to increase production. One of them is the technology development for rice age monitoring. In this paper, we presented the new method for Identified the growth phase of rice farming by using an Image from drone for information collecting in huge farming area. an Image data from drone is processed using an Image Processing method called Histogram of Color. After histogram information extracted, the data will be classified using machine learning called Support Vector Machine (SVM). the result of SVM is a classification of Rice farming's phase growth from pre-planting phase until harvesting phase. From the result of research, the accuracy of this method is about 93.3%.

Keywords: Rice Farming, Image Processing, Histogram, Machine Learning, SVM.

1. Introduction
Indonesia is well known as an archipelago country, also known by the world community as an agrarian country, where almost most of its land area is still used for agriculture and plantation purposes. As a country that has long struggled in agriculture and plantation, of course, has often faced with various inhibiting factors that can reduce the level of agricultural productivity. Various steps are taken to map agricultural productivity, from the simple way to the use of advanced technologies that exist today. The biggest agriculture in Indonesia is Rice Farming. It uses around 7.78 million hectares for planting. Because of this is the main food commodities, the government have to control the process of farming by collecting the data and manage it. Data collection methods are quite varied include: 1. can be done by plunging directly in the field as done in previous research, 2. can be done by taking data from a distance that can be done by downloading the data in the form of satellite images as in research [1,2,3,4,5], and 3. by implanting sensors in agricultural areas as in research [6,7] and then processing sensing data from different places and 4. can be done by taking data from a distance that can be done with how to use drone. For each method of data retrieval there are disadvantages and advantages. On the data collection by plunging directly in the field, will be a lot of time wasted because every farm should be visited one by one to get the data - the expected data. But this will be very different when using remote sensing methods, where the desired data can be obtained in a scale that is so broad and in a relatively short time. The obstacle in remote sensing is because the earth's atmosphere is not always clean from the clouds. Though clouds or other objects in the atmosphere can interfere with or make satellites cannot record events that exist on the surface of the earth.

In data collection methods that utilize the sensors grown in each agricultural area the results can be much better when compared with the first and second data collection methods because the tool has been installed in the location so that the accuracy of reading can be better and do not need to check the agricultural area one by one so it can save data collection time. But unfortunately, this third method
requires a lot of investment costs because the sensors must be installed in every agricultural area so in this study, the author uses only the first and second method. The first method of collecting data by plunging directly in the field will be used to cover the weakness of the second method of data collection by using remote sensing, when the earth’s atmosphere closed many clouds so it is not possible to do remote sensing.

The first method that existed in previous research developed a system for estimation of food crops production. it consists of android mobile applications as a tool of data collection in the field and web-based applications as a means of visualization monitoring the progress of plant growth which can be seen by the general public. The android mobile application has a function to calculate the area of agricultural land using GPS tracking, where the land is used to estimate the production of food crops. Haversine method is used to calculate the distance between corners of agricultural land and Polygonal method to calculate land area. Other supporting data such as the characteristics of each plant and information from farmers who already know the results of the production of land cultivated food crops for further use as a parameter to estimate the production. This first method is almost the same as the third method. From the results of the research, the accuracy of estimated food crop production reached 99.07%.

The second method is remote sensing using Landsat satellite imagery as an effort to facilitate data acquisition and estimation of agricultural production. Landsat satellite imagery is chosen because it has several advantages including: it can record the region on the surface of the earth on a larger scale, image data that can be obtained free of charge and provides various kinds of sensor channels with different functions that can be combined to obtain the best results in interpretation events occurring on the surface of the earth. While the weakness is almost the same in remote sensing methods general that is the use of highly weather dependent such as rain, clouds and fog caused by the operation from outer space where capturing still cannot penetrate the cloud. In addition, the maximum spatial resolution of only 15 meters makes it impossible to detect well the type of crop on the farm with the area of the planting area so small.

For the purpose method has the same data retrieval method with the third method is using the image. The image used in this method comes from a drone with a height of 500 meters. From this height one image data can cover ± 6 Ha.

2. Phase of Rice Growth

There are several phases that are carried out by rice plants since the early phases of growth to the harvest period with spectral signature varied when viewed using vertical views of images in between.

- Initial phase of rice growth, where rice fields are dominated by water due to inundation. In vertical view image with true color composite color composition (TCC), the rice field will appear blue.
- The vegetative growth phase, characterized by the increasingly dense leaves of rice plants covering all paddy fields. In this phase, land cover is dominated by green. This green color will look green on the image.
- Generative growth phase, where rice fields originally dominated by green leaves will be replaced with pale yellow rice grains on TCC.
- Harvest phase. In this phase the land becomes fallow for a period of time. In this condition the paddy fields will appear reddish brown on TCC color composition.

The phase of the harvest can be estimated using Landsat satellite imagery when referring to the average age of rice ranging from 110-120 days. This can be done by first monitoring the initial phase of planting, i.e. the change from the fallow phase (land preparation phase) to the water phase (soil / flooding) or by monitoring the phase change of the rice plant from the water phase to the vegetative phase.
3. Histogram and SVM Phase Rice Growth

3.1. Histogram

Histograms are widely applied in some cases. On [8] a histogram is used in the search space. In the study [9] the histogram was used to identify age through the face. The histogram technique is also used in [10] for health. A histogram is used to identify the shape of the study [11]. In the study [12] the histogram was used to identify genitals, hands (lefty or not) and the age of a handwriting. The histogram method is used to detect hand gestures. To find out the needs of the growth phase in rice plants, leaf color is the easiest indicator. Giving in the right amount and at the right time can provide a noticeable increase in absorption efficiency for the crops, thus getting the harvest as expected. The use of leaf color chart by equating the color of rice leaf with the color scale composed of green series, ranging from yellowish green to dark green accompanied by parameters is very important to facilitate the classification of the rice.

Leaf color chart (LCC) is a standard leaf color level issued by the International Rice Research Institute (IRRI). LCC commonly used to determine the nitrogen content of a plant so that later can be known when the time of fertilization and harvesting the right.

The use of cameras on drone drones in leaf shooting will help farmers to automatically determine the color level of plants, in this case helping the government in obtaining agricultural information based on LCC. In addition, manually farmers used BWD by comparing the color of plant leaves with each color level contained in the LCC. Determination of LCC level can be done automatically by utilizing the image so that the farmers can know the leaf image information is located at what level on the leaf color chart.

3.2. Support Vector Machine – SVM

Support Vector Machine (SVM) is first proposed for classification problems. SVM is used to analyze voltages [14]. In [15] also SVM is used for spectral-spatial. This is a supervised non-parametric statistical study technique. Therefore, the main advantage is that the distribution of the data does not need to be known priority, whereas other statistical techniques, for example, the maximum possible estimate usually assumes that the distribution of the data is known as a priority. To explain the concept of a supporting vector machine, a classification problem of two linear classes is used, see Figure 5. The purpose of a vector machine support technique is to find hyperplane separating data into many classes, which are two classes in this case. Such hyperplane is called decision bounders or hyper plane SVM. To
obtain a unique hybrid or optimal separation, a constraint with no data points at the hyperplane margin. The data points on the margin are called support vectors. In other words, support vectors are used for maximal hyperplane margin defects.

If data is not distributed linearly, using hyperplane cannot efficiently split data into many classes. To handle the distribution of non-linear data, the data is projected into a higher dimension space so that data points are distributed linearly in the new space. By using the appropriate projection function, products in a higher dimension space can be calculated in the original space without mapping the data points into a feature space that may have infinite dimensions through the use of the function of the batch.

3.3. "One-against-all" Method

Using this method, binary model S is constructed k (k is the number of classes). Each i-class model is trained using the entire data, to find the solution of the problem (1). For example, there is a classification problem with 4 classes. For training use 4 pieces of binary SVM as in table 1 and its use in classifying new data can be seen in Figure 6.

\[
\begin{align*}
\min_{w^i, b^i, \xi^i} & \quad \frac{1}{2} (w^i)^T w^i + C \sum_i \xi^i \\
\text{s.t.} & \quad (w^i)^T \phi(x_t) + b^i \geq 1 - \xi^i \rightarrow y_t = i, \\
& \quad (w^i)^T \phi(x_t) + b^i \geq 1 - \xi^i \rightarrow y_t \neq i, \\
& \quad \xi^i \geq 0
\end{align*}
\]

Figure 5. Illustration of concept vector supporting machine.

4. Case Study and Result

As mentioned earlier, the purpose of this study is to detect the growth phase of rice with the division of the rice group from 0 weeks to post-harvest. So that the information needs of a region can be seen from the taking of the image of rice by the drone device which then done the calculation of histogram value and determination of age group of rice using Support Vector Machine - SVM, with accurate calculation.
of histogram of each image, assist SVM in determining the age classification of rice, so the government can control the condition of the rice field area of an area with ease. The monitored variable refers to several RGB color variables from the rice image of each image retrieval using the drone device.

Some accuracy data measurements obtained do not produce 100% results, considering the color variables of each image is affected by sunlight and shooting height using the Drone device, but the accuracy obtained is 93.33%. The following is the process of running system design that is made using trainer data for rice age 3 to 4 months, as well as test data of 3-4 months, and predicts other test data with system error using test data for rice age 0-3 weeks.

The system design process runs describes image capture to calculate the histogram and stored in a database until testing the predicted age of rice using test data. The first step is to take the image of training data and then calculate the histogram and save the image data, in (figure 7). After the data is stored it will be in the process of testing the data using the test data that has been provided, performed the test image taking phase, then calculate the histogram, and load the data (figure 8) in the training phase using SVM (figure 9). Then the prediction will be done if the image data will be in accordance
with the test data that has not been in training by the system, if true then the data will display the age of rice in accordance with the image data that has been in training appropriately (figure 10), but if not successful will display results with improper commands (figure 11).

Of the 100 data available, 70 data were selected for training to represent each specified rice age then will be stored in the database, 30 other data provided for testing by doing data load, SVM training of image data, then calculated the histogram value and predicted data picture. Predicted accuracy of the data that has been tested will be determined by the assessment of true description in the total data for the test at 100%.

\[
Accuracy = \frac{Correct\ Prediction}{Data\ Total} \times 100\% \tag{5}
\]

For further experiment can be seen in the following table:

| No. | Data       | Rice Age Group (Y (original)) | Y (prediction) | True | False |
|-----|------------|------------------------------|----------------|------|-------|
| 1   | Figure 1   | 0 – 3 Week                   | 0 – 3 Week     | ✓    | -     |
| 2   | Figure 2   | 0 – 3 Week                   | 0 – 3 Week     | ✓    | -     |
| 3   | Figure 3   | 0 – 3 Week                   | 0 – 3 Week     | ✓    | -     |
| 4   | Figure 4   | 0 – 3 Week                   | 0 – 3 Week     | ✓    | -     |
| 5   | Figure 5   | 0 – 3 Week                   | 0 – 3 Week     | ✓    | -     |
| 6   | Figure 6   | 0 – 3 Week                   | 0 – 3 Week     | ✓    | -     |
| 7   | Figure 7   | 3 Week – 2 Month             | 3 Week – 2 Month| ✓    | -     |
| 8   | Figure 8   | 3 Week – 2 Month             | 3 Week – 2 Month| ✓    | -     |
| 9   | Figure 9   | 3 Week – 2 Month             | 3 Week – 2 Month| ✓    | -     |
| 10  | Figure 10  | 3 Week – 2 Month             | 3 Week – 2 Month| ✓    | -     |
| 11  | Figure 11  | 3 Week – 2 Month             | 3 Week – 2 Month| ✓    | -     |
| 12  | Figure 12  | 3 Week – 2 Month             | 3 Week – 2 Month| ✓    | -     |
| 13  | Figure 13  | 2 Month – 3 Month            | 2 Month – 3 Month| ✓    | -     |
| 14  | Figure 14  | 2 Month – 3 Month            | 2 Month – 3 Month| ✓    | -     |
| 15  | Figure 15  | 2 Month – 3 Month            | 2 Month – 3 Month| ✓    | -     |
| 16  | Figure 16  | 2 Month – 3 Month            | 2 Month – 3 Month| ✓    | -     |
| 17  | Figure 17  | 2 Month – 3 Month            | 2 Month – 3 Month| ✓    | -     |
| 18  | Figure 18  | 2 Month – 3 Month            | 2 Month – 3 Month| ✓    | -     |
| 19  | Figure 19  | 3 Month – 4 Month            | 3 Month – 4 Month| ✓    | -     |
| 20  | Figure 20  | 3 Month – 4 Month            | 3 Month – 4 Month| ✓    | -     |
| 21  | Figure 21  | 3 Month – 4 Month            | 3 Month – 4 Month| ✓    | -     |
| 22  | Figure 22  | 3 Month – 4 Month            | 3 Month – 4 Month| ✓    | -     |
| 23  | Figure 23  | 3 Month – 4 Month            | 3 Month – 4 Month| ✓    | -     |
| 24  | Figure 24  | 3 Month – 4 Month            | 3 Month – 4 Month| ✓    | -     |
| 25  | Figure 25  | Post-Harvest                | Post-Harvest   | ✓    | -     |
| 26  | Figure 26  | Post-Harvest                | Post-Harvest   | ✓    | -     |
| 27  | Figure 27  | Post-Harvest                | Post-Harvest   | ✓    | -     |
| 28  | Figure 28  | Post-Harvest                | Post-Harvest   | ✓    | -     |
| 29  | Figure 29  | Post-Harvest                | Post-Harvest   | ×    | -     |
| 30  | Figure 30  | Post-Harvest                | Post-Harvest   | ×    | -     |

5. Conclusion
From the experimental result using histogram and SVM calculation to know the growth phase of rice can be concluded:

1. The results obtained on the calculation of the image data of rice that is 93.33%, with errors obtained reach 6.67%, indicating that the proposed methodology successfully used.
2. Using the Histogram and Support Vector Machine methodologies, operators can quickly identify the age-growth stage of rice by utilizing images from drone devices to aid the government’s information needs.
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