

## Classification of Rice Growth Stage on UAV Image Based on Convolutional Neural Network Method

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### Abstract

Currently, the majority of the agricultural sector in Indonesia is carried out by small communities. Half of the Indonesian people (approximately 10 million people) work in the agricultural sector and utilize agricultural land. Some of the tools used by farmers are still using traditional tools, but some are already using modern farming tools. In general, agricultural tools are divided into 3 categories, namely agricultural tools used before the seeds are planted, agricultural tools used when caring for seedlings that are growing and developing, and agricultural tools used when harvesting. One of the technologies used in agriculture is the use of drones or Unmanned Aerial Vehicles (UAV) in the process of sowing fertilizers and seeds and spraying pesticides. The current use of UAVs supports agriculture with manual operation and based on GPS waypoint positioning. In the process, the visual aspects that can be obtained from the UAV have not been considered, so the treatment carried out on agricultural land is the same. The problem of similarity in treatment can lead to similar treatment on heterogeneous agricultural land. Agricultural land should be treated according to the conditions of the land. Because the condition of the land will affect the growth of the planted vegetation. Another problem found in agricultural land is the different rice growth in each paddy field. Rice growth can be seen by farmers through visual aspects but farmers cannot directly see the visual condition of rice growth as a whole because of the large area of land. Utilization of UAV by taking high-resolution aerial imagery can provide visuals of the overall condition of rice from various angles of image capture. The general objective of this research is to classify rice growth on high resolution UAV images based on the Convolutional Neural Network (CNN). The data used in this study were acquired using a multirotor UAV in the same rice field area. The data consists of 500 images consisting of 5 groups. Group 1-2 is the vegetative phase, group 3 is the generative phase and group 4-5 is the ripening phase. CNN is used to conduct training with variations of epochs are 100, 250 and 500. The best accuracy results are obtained in the training epoch 500 with 96% of Accuracy.

**Keywords** : classification, high resolution UAV imagery, deep learning, rice growth

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Received: 11-03-2023 | Revised: 30-03-2023 | Accepted: 31-03-2023  
DOI: <https://doi.org/10.23887/janapati.v12i1.60959>

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### INTRODUCTION

Currently, the majority of the agricultural sector in Indonesia is carried out by small communities. Half of the Indonesian people (approximately 10 million people) work in the agricultural sector and utilize agricultural land [1]. Some of the tools used by farmers are still using traditional tools, but some are already using modern farming tools. Broadly speaking, modern agricultural tools are divided into three categories. First, agricultural tools used before the seeds are planted. Second, the agricultural tools used when caring for seedlings are growing and developing. Third, agricultural tools used when harvesting [3]. The use of high and latest technology has begun to be used in the agricultural sector. One of the

technologies used is the use of drones or Unmanned Aerial Vehicles (UAV) in the process of sowing fertilizers and seeds and spraying pesticides [2]. The current use of UAVs in supporting agriculture is manually operated and based on GPS waypoint positions. In the process, the visual aspect that can be obtained from the UAV has not been considered so that the treatment carried out on agricultural land is the same. The problem of similarity in treatment can lead to similar treatment on heterogeneous agricultural land. Agricultural land should be treated according to the conditions of the land. Because the condition of the land will affect the growth of the planted vegetation.

Another problem found in agricultural land is the different rice growth in each paddy field. Rice growth can be seen by farmers through visual aspects but farmers cannot directly see the visual condition of rice growth as a whole because of the large area of land. Utilization of UAV by taking high-resolution aerial imagery can provide a visual of the overall condition of rice from various angles of image capture. High resolution images are obtained from the mosaic process of UAV image pieces, so that high resolution images are obtained for large agricultural land. The classification of the growth phase of food crops, especially rice, has been carried out by the Central Statistics Agency (BPS) based on a survey method, namely the area sample frame (KSA). The survey has a high estimation quality, however, it also has limitations, namely the high cost and lack of information on non-sampled areas [4]. The use of high resolution UAV imagery offers a cheaper solution and is carried out by visual observation in classifying rice growth. Classification can automatically apply methods based on Deep Learning methods. Classification can be performed on high resolution UAV image data. The classification process is carried out after preprocessing and segmentation. Previous research related to the use of paddy fields with UAV [5]–[9]. Research that uses Deep Learning method in doing classification, segmentation, pattern recognition [8]–[13].

Agricultural land is land that is intended or suitable to be used as agricultural land to produce agricultural crops and livestock [15]. Agricultural land is land that can also be used to grow rice. In rice cultivation there are three growth phases, namely the vegetative phase (0-60 days), the generative phase (60-90 days), and the ripening phase (90-120 days) [16].

UAV which stands for Unmanned Aerial Vehicle which literally means an aerial vehicle that operates without humans as its crew. UAVs are generally used by military units to monitor a situation where the use of a crewed aircraft is very risky. Based on the shape of the wings and body structure, UAVs can be grouped into two types, namely fixed-wing and rotary-wing. Fixed-wing is a type of aircraft that has a fixed wing shape, while rotary-wing is an aircraft that uses propellers to generate lift. In principle, when the aircraft is in the air, there are 4 main forces acting on the aircraft, namely the thrust (T), drag (D), lift (L), and the aircraft weight (weight W). When the plane is cruising at a constant speed and altitude, the 4 forces are in equilibrium:  $T = D$  and  $L = W$ . Meanwhile, when the plane takes off and lands, acceleration and deceleration occur which can be explained using Newton's second law (total force

is equal to mass multiplied by acceleration)[17]. High resolution UAV image is an image taken from a UAV device and processed with a mosaic so as to obtain a high resolution image with a large area.

Computer Vision is a process of transforming or changing data from video cameras or photos/images into a new decision or presentation, where the results of the transformation have an interest in achieving a goal. The data that is entered into the transformation activity makes it possible to have some contextual information such as a photo/image in which there are various objects. Thus, the decisions that will be taken on the image will be obtained. Unlike the case with humans who have the mind to research, understand, and compare information on objects directly with information from experiences gained during years of living in the world.

Research on image processing with Deep Learning has been carried out by previous research. [10] performed an analysis of the basic structure of the artificial neural network (ANN) and the CNN base network layer, the previous network model, the latest SOAT network algorithm, a comprehensive comparison of various image classifications. [18] detected rice fields with CNN YOLO on UAV imagery. [13] used a target detection algorithm in conducting experiments. The experimental results show that the application of a deep learning co product artificial neural network model in image processing can be improved more effectively by using the appropriate algorithm. [11] proposed an attractive model for a real-time image classification architecture based on deep learning with fully connected layers to extract precise features. [12] conducted a study on the use of machine learning in recognizing, detecting, classifying images in various fields.

Research on the development of UAVs has been carried out by researchers in research on designing prototypes of GPS-based C-UAV (courier unmanned aerial vehicle) devices [19]. In this research, a rotary hexa UAV was developed which can drop items according to the waypoint coordinates. [20] developed a fixed-wing UAV to be designed and manufactured using low cost materials with PID control. Based on the results of flight tests, a fixed-wing UAV has been successfully designed and manufactured with cheap materials and can fly autonomously following the trajectory command given using the PID compensator. [21] developed the Fixwing UAV which is used for monitoring and mapping natural disaster areas. [22] developed a low-cost instrumentation device capable of collecting data

on airspeed, aircraft orientation and altitude, and currents used by electrical systems.

Research related to UAV imaging has been carried out by researchers, namely UAV imaging in digital map making using a multicopter UAV in residential areas [23]. [6] Detecting the color of yellow rice that is ready for harvest was successfully carried out by processing HSV color, which was then detected by thresholding HSV with system testing errors of 3.1%, 8.7%, 4.9% and 248%. [5] estimated production by grouping images of agricultural areas using the K-Means method. This grouping uses HSV color parameters and Gabor textures as features of each part of the image.

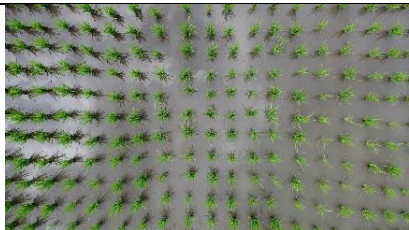


Research on classification and recognition of UAV imagery in agricultural areas was carried out by several previous researchers. [7] performed an object-oriented image classification applied to the image, combined with the texture size and image intensity, hue, and saturation (IHS), to achieve delineation. It was found that the inclusion of near-infrared (NIR) and red-green-blue (RGB) spectra, in combination with texture or IHS, increased classification accuracy for single and mosaic images to above 94%. [8] estimated rice yields by segmenting grain areas using low-altitude RGB images collected using a rotary wing-type UAV. In



particular, an image processing method that combines K-means clustering with a graph-cut algorithm (KCG) is proposed to segment the grain area. [9] introduced a new vegetation segmentation methodology for low-cost RGB UAV images, which relies on the use of the Hue color channel. Based on the problems that have been studied and the methods used in the previous research, this research proposes a research on Classification of Rice Growth Stage on UAV Image Based on Convolutional Neural Network Method.

#### MATERIAL AND METHOD

The material used in this research is UAV images in rice fields. Image data was acquired using a Multicopter UAV with DJI MAVIC Mini I Type. The results obtained in the data acquisition were in the form of video in MP4 format. The video data is then extracted into image frames. The extracted image has a High Definition resolution of 1920x1080 pixels. The data consists of 500 images consisting of 5 groups. Group 1-2 is the vegetative phase, group 3 is the generative phase and group 4-5 is the ripening phase. The datasets are shown in Table 1. The dataset is not added pre-processing or post-processing.

Table 1. Dataset Descriptions

Name	Quantitation	Image Sample
Group 1	100	
Group 2	100	
Group 3	100	

Name	Quantitation	Image Sample
Group 4	100	
Group 5	100	

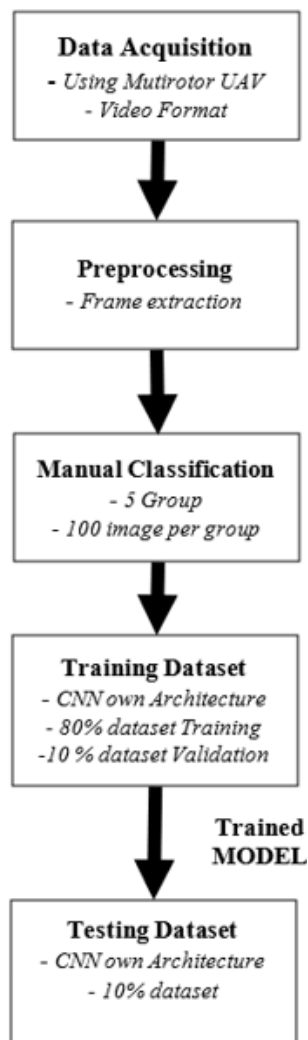


Figure 1. Research Method.

The method used in this study is shown in Figure 1. The sample of image Dataset show on Table 1. The image is result of the frame extraction step. The Dataset is divide into 3 Dataset, that is 80% on Training Dataset, 10% Validation Dataset, 10% Testing Dataset. The training process using the Convolutional Neural Network (CNN). The Architecture of CNN show on Figure 2.

The dataset that has been labeled in the previous stage will be trained to produce a model

that will be used in the Testing process. The model formed is a model that already has a pattern whose results are in the form of weights. These weights will be used in the Testing process. The number of images used for training is 400 training images, validation data is 50 images, testing data is 50 images. The sample of Training and validation data is shown on Figure 3.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 198, 198, 16)	448
max_pooling2d	(MaxPooling2D (None, 99, 99, 16)	0)
conv2d_1 (Conv2D)	(None, 97, 97, 32)	4640
max_pooling2d_1	(MaxPooling (None, 48, 48, 32)	0 2D)
conv2d_2 (Conv2D)	(None, 46, 46, 64)	18496
max_pooling2d_2	(MaxPooling (None, 23, 23, 64)	0 2D)
flatten (Flatten)	(None, 33856)	0
dense (Dense)	(None, 512)	17334784
dense_1 (Dense)	(None, 5)	2565

Figure 2. CNN Architecture

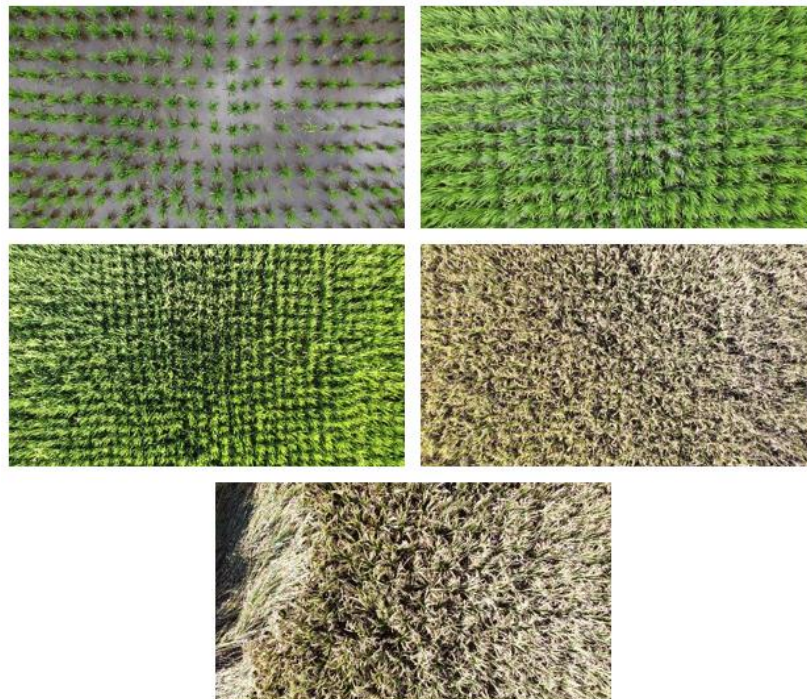


Figure 3. Sample of Training and Validation Dataset.

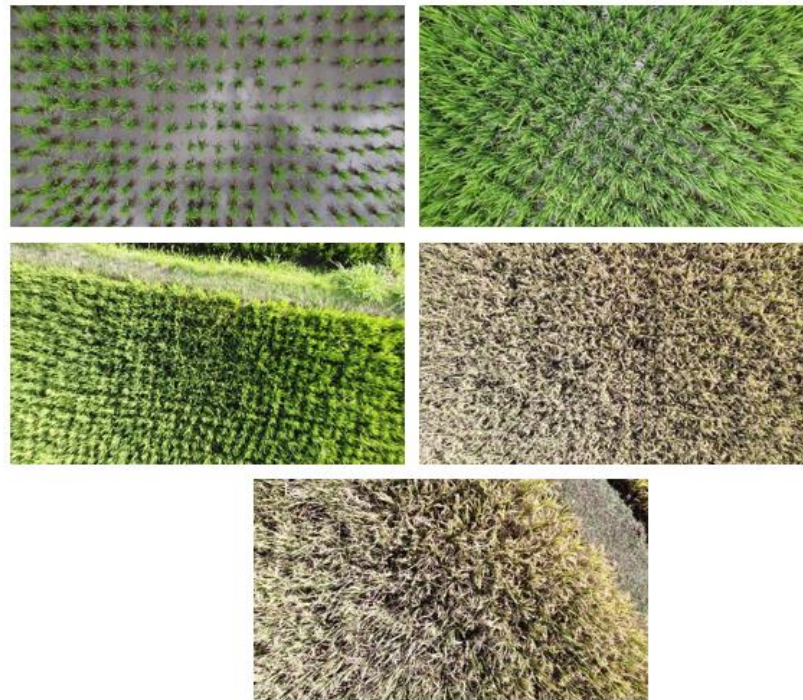


Figure 4. Sample of Testing Dataset.

Testing dataset is used to determine the capability of the architectural model generated in the training process. At this stage, 50 images were used to be a testing dataset. The sample of Testing dataset is shown on Figure 4.

Measurements made in the testing process are using accuracy measurements and confusion Matrix shown on Figure 5.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Figure 5. Confusion Matrix.

Accuration is the ratio of True (positive and negative) predictions to the overall data.

$$Acc = (TP + TN) / (TP + FP + FN + TN) \quad (1)$$

## RESULT AND DISCUSSION

In this section, the results and discussions will be described. The results of the data acquisition and its distribution to the Training, Validation and Testing data are shown in Figure 3 and Figure 4. After the Training, Validation and Testing dataset is formed. Then training is carried out on the Training dataset. Training uses CNN Architecture in Figure 2. The epoch variations used are 100, 250 and 500 epochs. Snippets of Training Results are shown in Figure 6. Using the graphic, we can show the pattern of the training result. The Training Results are shown in Figure 7.

```

4/4 [=====] – ETA: 0s – loss: 5.6690 – accuracy: 0.33332022
Epoch 2/250
4/4 [=====] – ETA: 0s – loss: 2.0247 – accuracy: 0.25002022
.....
Epoch 249/250
4/4 [=====] – 4s 1s/step – loss: 2.6401e-04 – accuracy: 1.0000
Epoch 250/250
4/4 [=====] – 4s 1s/step – loss: 1.7460e-04 – accuracy: 1.0000
  
```

Figure 6. Snippets of Training Results.



Figure 7. Training Result.

Table 2. Result of 100 variation epoch.

Group	Group 1	Group 2	Group3	Group 4	Group 5	True	False
Group 1	10	0	0	0	0	10	0
Group 2	0	10	0	0	0	10	0
Group 3	0	0	10	0	0	10	0
Group 4	0	0	0	4	6	4	6
Group 5	0	0	0	0	10	10	0
					Total	44	6

Table 3. Result of 250 variation epoch.

Group	Group 1	Group 2	Group3	Group 4	Group 5	True	False
Group 1	10	0	0	0	0	10	0
Group 2	0	10	0	0	0	10	0
Group 3	0	0	8	2	0	8	2
Group 4	0	0	0	10	0	10	0
Group 5	0	0	0	4	6	6	4
					Total	44	6

Table 4. Result of 500 variation epoch.

Group	Group 1	Group 2	Group3	Group 4	Group 5	True	False
Group 1	10	0	0	0	0	10	0
Group 2	0	10	0	0	0	10	0
Group 3	0	0	10	0	0	10	0
Group 4	0	0	0	10	0	10	0
Group 5	0	0	0	2	8	8	2
					Total	48	2

Based on the results of the calculation of accuracy on the variations of epoch 100, 250 and 500, the accuracy of epoch 100 is 88%, epoch 250 is 88% and epoch 500 is 96%.

The results of the calculation table for the accuracy of each variation of epoch 100, 250, 500 are shown in Table 2, Table 3, Table 4. In the variation of epoch 100, there are 4 group 4 images classified in group 5 images. group 5 images have the same phase. In the 250 epoch variation there are 2 group 3 images classified in group 4, and 4 group 5 images classified in group 5. In variation 500, there are 2 group 5 images classified in group 4.

### CONCLUSION

This study proposes the Convolutional Neural Network method in classifying rice growth. The method proposed in this research is Data Acquisition, Preprocessing, Manual

Classification, Training Dataset, Testing Dataset. The dataset that has been labeled in the previous stage will be trained to produce a model that will be used in the Testing process. The model formed is a model that already has a pattern whose results are in the form of weights. These weights will be used in the Testing process. The number of images used for training is 400 training images, validation data is 50 images, testing data is 50 images. Based on the results of the calculation of accuracy on the variations of epoch 100, 250 and 500, the accuracy of epoch 100 is 88%, epoch 250 is 88% and epoch 500 is 96%.



## ACKNOWLEDGMENT

We would like to thank to Research institutions and community service Universitas pendidikan Ganesha and Ministry of Research, Technology and Higher Education Indonesia. This research was financially supported by Scheme Penelitian Dasar Unggulan Perguruan Tinggi (PDUPT) 2022 Ministry of Research, Technology and Higher Education Indonesia.

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