Performance Comparison between Convolutional Neural Network and Supervised Multiresolution Segmentation for Actual Paddy Planted Area

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Abstract

Malaysians' yearly rice demand has reached 2.5 million metric tonnes, whereas the country's rice production is only about 70% of the overall need. To compensate for the country's rice output deficiency, the government must import 700,000 to 900,000 metric tonnes of rice each year. Due to several factors, including severe climate change, other more profitable alternative crops, and high production costs, rice harvests vary from season to season. Furthermore, determining and monitoring typical paddy fields will entail field surveys, which will require a considerable financial commitment, a significant amount of time, and will not be thorough. Thus, with space technology and computer analysis of satellite images, the rice crop area may be estimated rapidly, precisely, and exhaustively. There are several digital image processing approaches to determine the precise location of paddy crops, which are quicker than traditional site surveys. The goal of this study is to compare the results of segmentation for actual paddy planted areas in Sungai Besar, Selangor, acquired from the Pleiades satellite at a spatial resolution of 0.5 m using the Convolutional Neural Network (CNN) method to the results obtained using the Multiresolution Segmentation (MRS) method. While the MRS results show Kappa = 0.6046 and Overall Accuracy = 0.820, the CNN segmentation results show Kappa = 0.8792 and Overall Accuracy = 0. 920. The outcomes show that the CNN approach can be used successfully and will be the most important factor in long-term problem solving.

Keywords: Paddy, Convolutional Neural Network (CNN), Multiresolution segmentation (MRS), Pleiades

1.0 INTRODUCTION

The principal staple food and food crop of Malaysia, paddy and rice, have been the focus of the country's self-sufficiency policy. In 2017, an average Malaysian consumes about 74.4 kilograms of rice per year (MOA, 2017). Meanwhile, 2.9 million metric tons of rice were produced in 2019 from 684 416 hectares of paddy cultivation area in Malaysia (DOA, 2019). Despite the high production, Malaysia's self-sufficiency level is only between 60-70 percent, forcing Malaysia to import the remaining percentage from Thailand, Vietnam, and Pakistan. The impacts of land use change from paddy cultivation area to commercial uses increase the challenge to achieve food security and increase paddy yields in the future. As a result of this problem, the Malaysia Space Agency (MYSA) and the Department of Agriculture Malaysia (DOA) partnered to develop the Paddy Geospatial Information System (MakGeoPadi), which identifies the precise areas of paddy production throughout Malaysia.

The MakGeoPadi system's primary purpose is to estimate the size of paddy fields, which highlights the significance of creating an accurate classification of paddy fields. The main function of the MakGeoPadi system is to determine the area of paddy fields, which emphasises the importance of producing a precise paddy segmentation. Segmentation of paddy lot into two categories which are; i) cultivated and ii) non-cultivated areas in fields is critical due to the frequent change of land use annually. To date, manual annotation through visual digitization of high-resolution satellite images is used to determine the type of land use in paddy fields. This method is less favourable because it highly depends on the expertise of individuals to segment the satellite images of the paddy fields, hence an automatic approach is needed.

Nowadays, deep learning models have recently drawn a lot of attention from the remote sensing communities because they are known to deliver exceptional performance in a variety of applications Deep learning (DL) is a sub-learning method under Machine Learning (ML). DL techniques are essentially Neural Networks but with three or more layers. According to Buduma and Locascio (2017), DL is capable of learning large amounts of data and solving a variety of difficult problems when compared to other ML techniques. The commonly used DL algorithm is Convolutional Neural Network (CNN) (Zhu et al. 2019). CNN is a DL visual processing technique that is very suitable for image pattern detection and able to achieve higher speeds than with common ML methods. In other hand, multi-resolution segmentation is a kind of ML. It is a bottom-up region merging technique that is based on a local homogeneity criterion, describing the similarity of adjacent image objects. The homogeneity criterion depends on the "suitable" or "unsuitable" criteria and the "combination cost" reserved for each possible combination and this cost representing the degree of assembly. Assembly levels are evaluated and joins are met until no more joins are possible. Thus, the "homogeneity criterion" is achieved. Following is the problem statements and objectives of this study.

Problem statement:

1. How does the paddy area mapping model based on a deep learning can help identification and estimation?
2. How are the results measured to confirm the performance level of the model developed?

Objectives:

1. To segment a map of paddy cultivation area into 2 categories which are cultivated and non-cultivated areas within paddy parcel (active paddy parcel (PA) and miscellaneous paddy parcel (PT), and non-paddy areas (N).
2. To compare the accuracy of two techniques, namely Convolutional Neural Network (CNN) and Multiresolution Segmentation (MRS) to produce a mapping model for segmentation of cultivated and non-cultivated paddy areas of Sungai Besar in Barat Laut Selangor Integrated Agricultural Development Area.

2.0 METHODOLOGY

2.1 Study Area

Bagan Terap, a locality in Integrated Agriculture Development Area (IADA) Barat Laut Selangor, Malaysia is used as the testing area for this study (Figure 1). This flat topography granary area covers approximately 1615 hectare of cultivated paddy area and a wide variety of uncultivated paddy areas including oil palm, vegetables, fruits and also including houses and roadways (Sistem MakGeoPadi, 2022). Due to a structured irrigation system this unique short-term crop is planted twice a year. This fertile area is among the highest rice producers in Malaysia which produce about 159 535 metric tonnes in 2020 (DOA Malaysia, 2021).

Figure 1: Bagan Terap of IADA Barat Laut Selangor Granary Area

2.2 Data Collection

Pleiades satellite image are acquired consist of cultivated and non-cultivated paddy area. Pleiades pre-processing including re-project and enhancement is done using ArcMap 10.6.1 and Erdas Imagine.

2.3 Cultivated and Non-Cultivated Paddy Area

In this study, individual paddy lot is segmented into two (2) categories, i) cultivated (the planting area) and ii) non-cultivated areas (ploughing, irrigating, and harvesting area, permanent structures, and permanent crop such as oil palm and rubber). The segmentation result is used as samples for CNN classification.

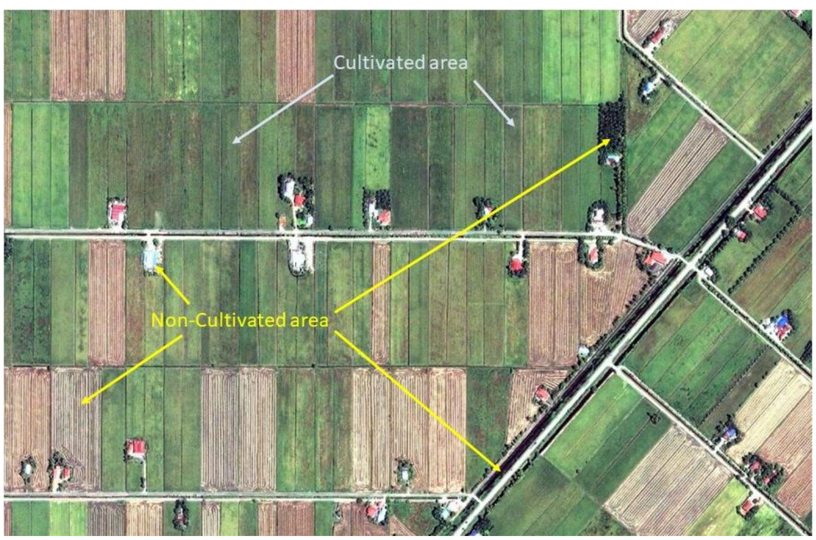

Figure 3: Cultivated and Non-Cultivated Paddy Area

2.4 Convolutional Neural Network

Deep learning methods work incredibly well for semantic segmentation, which tries to categorise each pixel into a class of things or non-objects. In addition, semantic segmentation is critical for image interpretation and image analysis tasks, and as such, it can produce precise and faster segmentation output (M. Pashaei et al, 2020). The main goal of this work is to semantically segments the Pleiades satellite images into two (2) categories, i) cultivated (the planting area) and ii) non-cultivated areas (ploughing, irrigating, and harvesting area, permanent structures, and permanent crop such as oil palm and rubber). To fit the Convolutional Neural Network architecture, the high-resolution satellite images are split into smaller patches of 64 × 64 pixels as sample datasets. The final output channel contains the category prediction of the pixel of the corresponding spatial position. Our CNN model has 16 CONV layers and 1 fully connected layer. Architecture of CNN was represented in Figure 4. In this CNN segmentation, 10000 sample patches (of 64 × 64 pixels) have been generated based on sample data for cultivated and non-cultivated areas covering the study area. 70% from total patches then were used as train sample for CNN meanwhile the remaining 30% were used to validate the output.

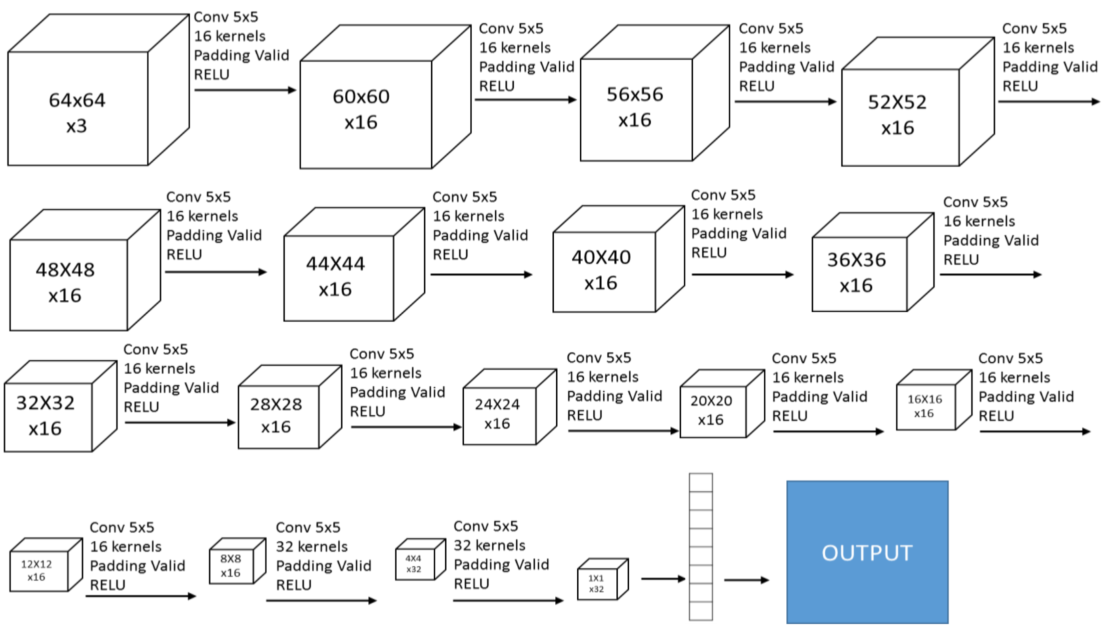

Figure 4: Architecture of CNN

Figure 5: Sampels for CNN

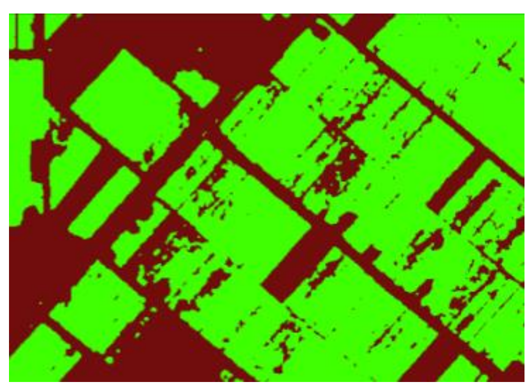

Figure 6: CNN segmentation result

2.5 Supervised Multiresolution Segmentation

In this study eCognition Developer software is used as segmentation and classification tools. It consists of three user-selected parameters: scale, shape and compactness parameters. The scale parameter determines the maximum relative boundary length of sub-objects to neighbours, which are not subjects of the same superior object. Since it has a limited effect on the construction of image objects, the shape and compactness parameters are taken as 0.1 and 0.5, respectively, as suggested by many studies. First, the study area image is segmented using the multiresolution segmentation using parameter scale = 50, shape = 0.1 and compactness = 0.5. The result of the segmentation as shows in Figure 5. From the segmentation, 600 polygons are selected as samples (cultivated and non-cultivated) for classification. In Figure 5, the green polygons refer to the cultivated area and the red polygons refer to the non-cultivated area while the black polygon is the segmentation. Next, the standard Nearest Neighbour Classification is implemented and the result is shows in Figure 6, which the green polygon is the cultivated area meanwhile the red polygon is the non-cultivated area. The overall processing flowchart of multiresolution segmentation as shows in Figure 9.

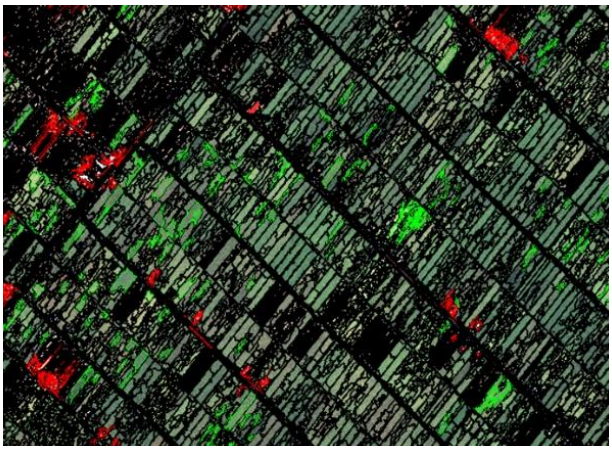

Figure7: eCognition Multiresolution Segmentation (scale = 50, shape = 0.1 and compactness = 0.5)

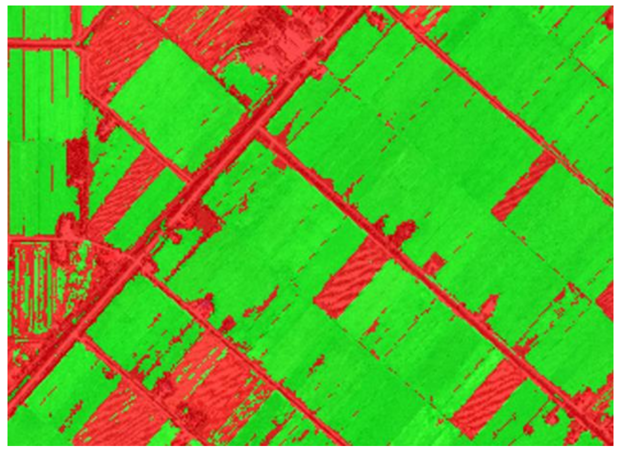

Figure 8: eCognition Nearest Neighbor Classification

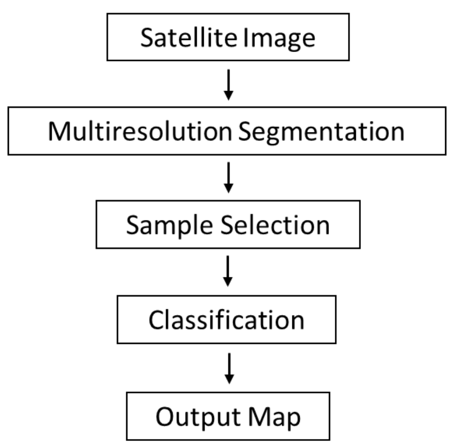

Figure 9: eCognition Multiresolution Segmentation Flowchart

2.6 Accuracy Assessment

2.6.1 Convolutional Neural Network

The CNN model architecture, which have 16 CONV layers and followed by FC layers has been used to produce cultivated and non-cultivated paddy segmentation from the RGB layers of Pléiades image.

The accuracy assessment for cultivated and non-cultivated paddy area was performed using 50 random location generated for data validation. It showed that the producer and user accuracies as well as the Kappa statistics were then computed. Generally, CNN recorded promising result and showed as follows

Table 1: Contingency Matrix for CNN Segmentation

VERIFICATION	**Non-Cultivated Area**	**Cultivated Area**	**Total**
Non-Cultivated Area	19	1	20
Cultivated Area	3	27	30
Total	**22**	**28**	**50**

Out of 50 samples, 40 were classified as correct. The kappa statistics values indicate that the result calculated was substantial as shown as:

Kappa values, K = (Po - Pc) / (1 - Pc)
= (0.940 - 0.5032) / (1 - 0.5032)
= 0.8792

Observed agreement, Po = (19+28) / 50
= 0.940

Expected agreement, Pc = [(22/50) x (19/50)] + [(28/50) x (30/50)]
= 0.5032

The kappa statistic is a measure of how closely the instances classified by the machine learning classifier matched the data labelled as ground truth, controlling for the accuracy of a random classifier as measured by the expected accuracy. The interpretation of Kappa results is as shown in Table 3.

Table 2: Kappa Values Indicator

Kappa values	**Description**
≤ 0	no agreement
0.01–0.20	none to slight
0.21–0.40	fair
0.41– 0.60	moderate
0.61–0.80	substantial
0.81–1.00	almost perfect agreement

2.6.2 Supervised Multiresolution Segmentation

The accuracy assessment for cultivated and non-cultivated area was performed and stratified random sampling of 50 data locations were randomly selected. Verification was performed by using Pleiades images (0.5 meters) resolution. It showed that the producer and user accuracies as well as the Kappa statistics were then computed showed as follows

Table 3: Contingency Matrix for MRS Segmentation

VERIFICATION	Non-Cultivated Area	Cultivated Area	Total
Non-Cultivated Area	13	5	18
Cultivated Area	4	28	32
Total	**17**	**33**	**50**

Out of 50 samples, 41 were classified as correct. The kappa statistics values indicate that the result calculated was substantial as shown as:

Kappa values, K = (Po - Pc) / (1 - Pc)
= (0.8200 - 0.5448) / (1 - 0.5448)
= 0.6046

Observed agreement, Po = (13+28) /50
= 0.8200

Expected agreement, Pc = ((17/50) x (18/50)) + ((33/50) x (32/50))
= 0.5448

3.0 RESULT AND DISCUSSION

This project focused on comparing CNN with MRS approaches. The result shows that the cultivated and non-cultivated paddy area can be classified using the CCN and MRS. The CCN showed more promising result with overall accuracy 0.920 (kappa =0.8792) whereas MRS learning procedure recorded 0.8200 (kappa=0.6046) in mapping paddy cultivation areas as shown in the table below.

Table 4: Kappa and Overall Accuracy for CNN and MRS method

Method	CNN	MRS
Validation sample	50	50
Kappa	0.8792	0.6046
Overall Accuracy	0. 920	0.820

In general, the results of the segmentation accuracy analysis for CNN are better than MRS. From the output map produced, CNN shows better results where non-cultivated paddy can be segmentize within cultivated area as seen in Figure 10.

To obtain the highest efficiency, the researcher will enhance the CNN by adopted other method such as Support Vector Machine (SVM) parameters. In future the project will also focuses in mapping different growth stages as well as mapping paddy pest and disease effected areas. It also will continue in assessing CNN technique in fertiliser application in paddy cultivation.

In terms of CNN protocol and method advancement, CNN technology is fast improving in terms of making image processing protocols more convenient and less manual. Future study will concentrate on the following areas. To begin with, this method will be used to a variety of imageries, such as high spatial resolution satellite images. Second, the proposed technique will be compared to existing segmentation methods such as dual clustering and partial differential equation-based methods. This method could be utilised as a teaching tool for assistants as well as a pre-processing step for other automated methods on low spatial resolution data sets.

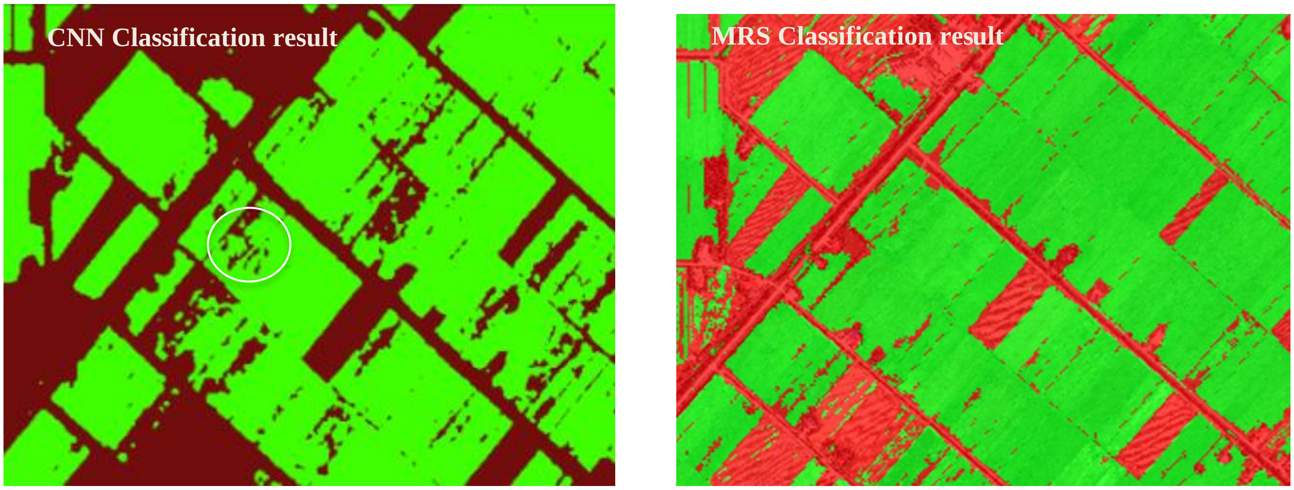

Figure 10: Classification result for CNN and MRS

4.0 CONCLUSION

In summary, this study has started the investigation into the use of DL for monitoring paddy lands by mapping the area using satellite data images and categorising them. CNN produces a good result for mapping cultivated and non-cultivated paddy at plot level with accuracy of 0.9697. Some limitations like cloud cover, shadow and image background require other sources of information to be labelled correctly. Various aspects in preparing training data can be explored in the future in improving the deep learning semantic segmentation result. Based on the findings from the use of CNN deep learning, we have successfully achieved the research objectives. By using the paddy area mapping model created for this study, it is hoped that responsible agencies will be able to use it and investigate ways to improve paddy production in our nation. Additionally, this entire study can be used as a main reference that can be benefited by present and future generations.

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