LAND COVER CLASSIFICATION FOR ECONOMIC CROPS IN THAILAND USING CONVOLUTIOINAL NEURAL NETWORKS

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ABSTRACT: Agriculture is one of the most important to the Thai economy. Agriculture in Thailand is very competitive and diverse. Thailand's exports of agricultural products are particularly successful on an international level and the economic crops in Thailand are rice, cassava, maize, para-rubber, sugar cane, and oil palm. Updated and reliable information on economic crop areas at a country level is important for the short and long-term planning and management of the Thailand government and related agencies. Deep learning with convolutional neural networks has been successfully applied in many remote sensing applications; especially in land use and land cover classification. This research aims to develop the methodology based on convolutional neural networks to classify economics crops at the country scale. We have used multiple Landsat-8 (OLI) images during 2015-2017 as the dataset. We have systematically sampled the training and testing data covering almost parts of Thailand. We have employed convolutional neural networks and designed the layers and parameters that are suitable for the Landsat-8 images and economic crops to classify the land cover areas. In the experimental results, our proposed method based on convolutional neural networks provided the prominent classification accuracy of 97% with the Kappa coefficient of 0.91. While, the other methods provided the accuracies and Kappa coefficients of 60% and 0.31 for Maximum likelihood, 87% and 0.57 for Support vector machine, and 92% and 0.76 for Multilayer perceptron neural networks. However, it made the slower computing time than the other methods.

1. INTRODUCTION

In Thailand, Agriculture is highly competitive and diversified. Agriculture exports are very affluent. Rice is the country's most important crop, with around 60% of 13 million farmers and it is totally half of cultivated land (Bangkok post, 2017). In 2014, rice exports amounted to 1.3% of GDP. Agricultural production estimated about 9-10.5% of GDP. Around 40% of the population work in agriculture-related occupations (The world bank, 2016). Thailand is considered as a huge exporter for agricultural products. The main economic agricultural products are rice, cassava, maize, para-rubber, sugar cane, and oil palm. Therefore, updated and reliable information on economic crops at a country level is essential for management and planning for government, and relevant organizations to increase economic growth.

The image analysis of remotely sensed data is very important in several applications, especially land cover classification. The land cover classification considers the given spectrum to assign it to a certain class. A variety of classification algorithms have been developed such as maximum likelihood (Le Cam, 1990), Mahalanobis distance (De Maesschalck et.al, 2000), random forest (Breiman, 2001), support vector machine (Meyer, 2003), and neural network (Graupe, 2013). For example, Al-Razzaq Abd used Maximum likelihood classification to produce land use and land cover map. The Mahalanobis distance was applied to classify land cover areas (Sritarapipat, 2015). Pal and Mather (, 2015) employed support vector machine to obtain land cover map. Neural networks with multi-layer perceptron were performed to provide land cover images (Civco, 1993). Deep learning with convolutional neural networks was proposed to classify land cover areas (Wan et.al, 2019). Convolutional neural networks have been widely used for a high-resolution image such as GeoEye images, WordView (Zhang et.al, 2018), However, convolutional neural networks have been rarely used for medium-resolution images such as Landsat images.

In this research, we developed land cover classification method using convolution neural networks for the economic crops in Thailand using Landsat-8 multispectral images. We designed the convolutional neural networks based on LeNet-5 (Le Cun et.al, 1998) to be suitable for classifying land cover areas for economic crops from Landsat images.

2. METHODOLOGY

2.1 Study area and materials

The focused area in this research is the whole area of Thailand. Thailand has the land area of 510,890 square kilometers and the water area of 2,230 square kilometers also the total area of 513,120 square kilometers (the 51st largest nation in the world). Thailand is a large exporter for agricultural products with the main economic agricultural products of rice, cassava, maize, para-rubber, sugar cane, and oil palm. In this research, 43 multispectral images during 2015-2017 acquired by Landsat 8 satellite (OLI) were used as dataset. The images have a spatial resolution of 30 m. and 11 spectral bands. However, we only used 7 spectral bands with Band 1 – Coastal Aerosol, Band 2 – Blue, Band 3 - Green, Band 4 - Red, Band 5 - Near Infrared (NIR), Band 6 - Short-wave Infrared (SWIR) 1, Band 7 - Short-wave Infrared (SWIR) 2.

2.2 Methods

Firstly, we sampled the data of nine classes from 43 Landsat 8 images. Then, the data are separated into two groups; training data and testing data. Here, we designed the convolutional neural networks to be suitable for classifying land cover areas for economic crops from Landsat images. Then, we applied the testing data with the supervised classification methods with the convolutional neural networks. We employed the testing data with the classifiers to obtain the results of land cover areas. Next, we validate the results of land cover areas with the referenced land cover areas as testing data to calculate the accuracies. The flowchart of our methods to obtain the accuracies of land cover classification methods is illustrated in figure 1.

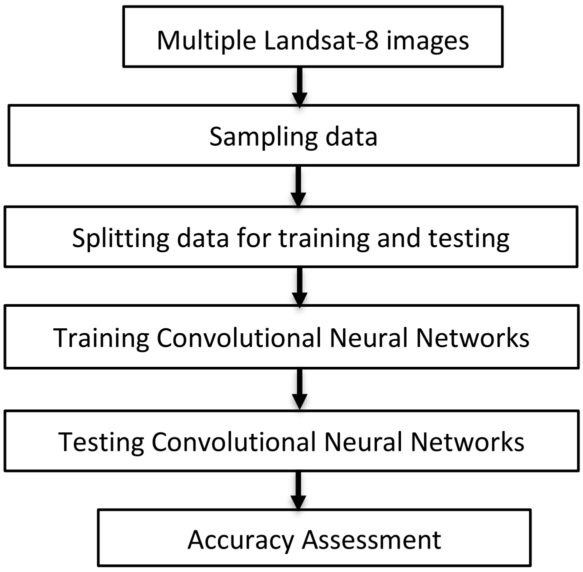

Figure 1 The flowchart of our methods to obtain the accuracies of land cover classification methods.

2.2.1 Sampling data

We sampled the data of nine classes with (1) urban, (2) water, (3) forest, (4) rice, (5) cassava, (6) maize, (7) para-rubber, (8) sugar cane, and (9) oil palm with the systematic regions from 43 multi-spectral images acquired by Landsat 8 by using visual interpretation. The total sampling pixels are 20,132,734. The regions of sampling data are shown in figure 2.

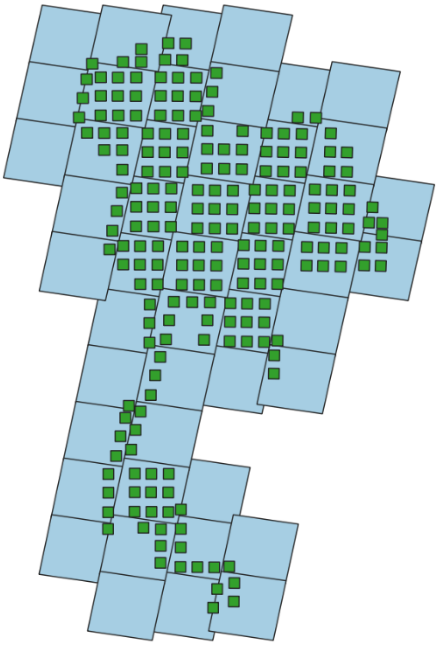

Figure 2 The regions of sampling data that covers Thailand.

2.2.2 Splitting training data and testing data

The sampling data were separated into two groups with (1) training data with 20% and (2) testing data with 80%. The training data are 4,026,547 pixels and the testing data are 16,106,187pixels.

2.2.3 Convolutional neural networks

We designed the convolutional neural networks based on LeNet-5 (Le Cun et.al, 1998) to be suitable for classifying land cover areas for economic crops from Landsat images. The model includes five hidden layers. The input is 8x8 (pixels) x7 (bands). The convolution layer 1 is 2x2 (pixels) x16 (filters). The pooling layer 1 is 2x2 (pixels). The convolution layer 2 is 2x2 (pixels) x32 (filters). The pooling layer 1 is 2x2 (pixels). The fully connected layer is 128 (nodes). The output layer is 9 (nodes). Adam algorithm was used to optimize the model.

2.2.4 Accuracy assessment

the multiple accuracy indexes were calculated with (1) overall accuracy, kappa coefficient, confusion matrix, accuracy in each class, and time computing process.

2.2.5 Comparison with other methods

We compared the results of land cover classifications using Convolutional neural networks with other methods; Maxim likelihood, Support vector machine, Multi-layer perceptron neural networks.

3. RESULTS AND DISCUSSIONS

In the experiments, there are 10 experiments with (1) maxim likelihood, (2) support vector machine using linear kernel (3) support vector machine using linear kernel, and principle component analysis, (4) neural network using multi-layer perceptron with 1 hidden layer composed of 100 nodes (5) neural network using multi-layer perceptron with 2 hidden layer composed of 100 nodes in each hidden layer, (6) neural network using multi-layer perceptron with 3 hidden layers composed of 100 nodes in each hidden layer, (7) neural network using multi-layer perceptron with 4 hidden layer composed of 100 nodes in each hidden layer, (8) neural network using multi-layer perceptron with 4 hidden layer composed of 100 nodes in each hidden layer that was calculated by using graphic processing unit (GPU), (9) convolution neural networks with input 7x7 pixels by using GPU, (10) convolution neural networks with input 8x8 pixels by using GPU.

3.1 Results

Table 1 shows the comparison of the overall accuracies of land cover classification methods and the Kappa coefficients and computing times. The bar graph in figure 3 illustrates the comparison of the overall accuracies of land cover classification methods. The bar graph in figure 4 demonstrates the comparison of the Kappa coefficients of land cover classification methods. The bar graph in figure 5 shows the comparison of the computing times of land cover classification methods.

Table 1 The comparison of the overall accuracies, the Kappa coefficients and the computing times of land cover classification methods

No	Method	Overall accuracy	Kappa coefficient	Computing time
1	Maximum likelihood	29.60%	. 0.3108	0 min. 35 sec.
2	SVM linear	87.10%	0.5705	43 min. 42 sec.
3	PCA + SVM linear	86.96%	0.5387	28 min. 12 sec.
4	Neural network MLP 1 layer	89.56%	0.6657	7 min. 6 sec.
5	Neural network MLP 2 layers	90.87%	0.7294	27 min. 14 sec.
6	Neural network MLP 3 layers	91.26%	0.7288	27 min. 41 sec.
7	Neural network MLP 4 layers	91.83%	0.7552	51 min. 11 sec.
8	Neural network MLP 4 layers (GPU)	90.16%	0.6959	20 min 58 sec.
9	Convolutional Neural network input 7x7 (GPU)	96.38%	0.8992	22 Hr. 9 min. 5 sec.
10	Convolutional Neural network input 8x8 (GPU)	96.93%	0.9141	24 Hr. 48 min. 42 sec.

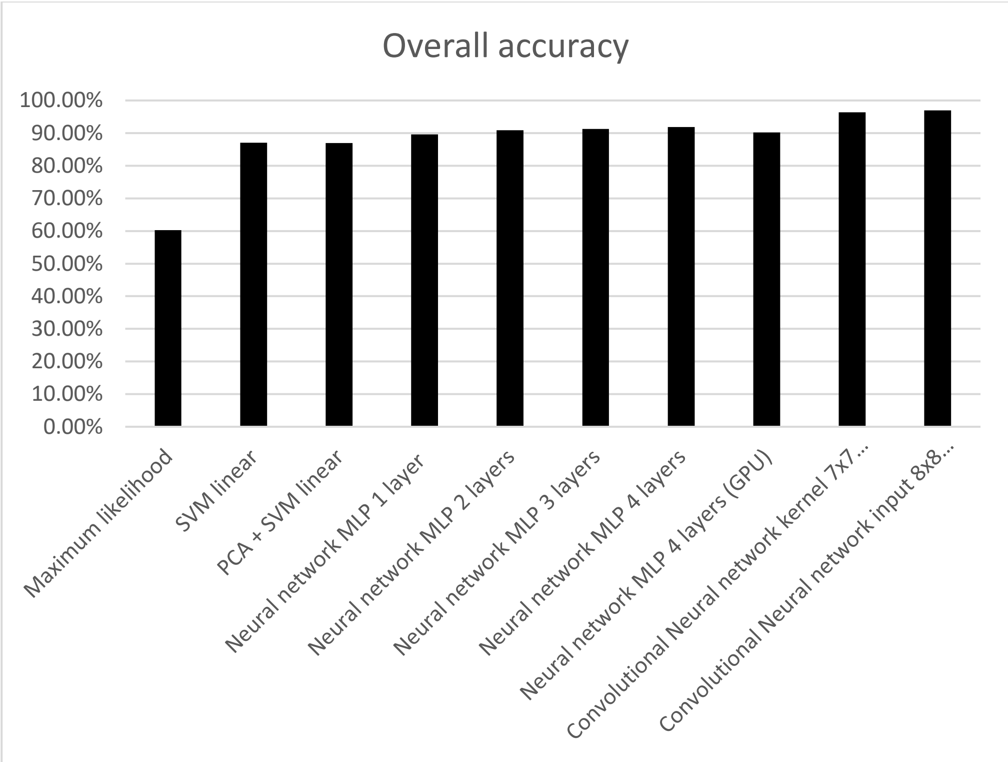

Figure 3 The comparison of the overall accuracies of land cover classification methods

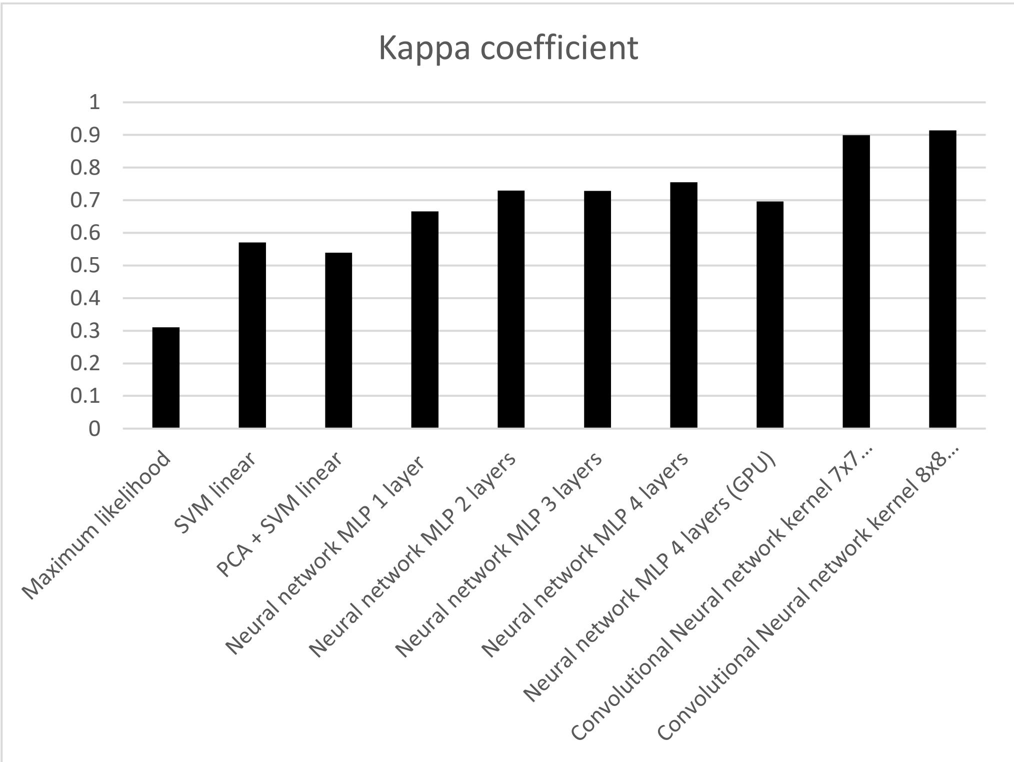

Figure 4 The comparison of the Kappa coefficients of land cover classification methods

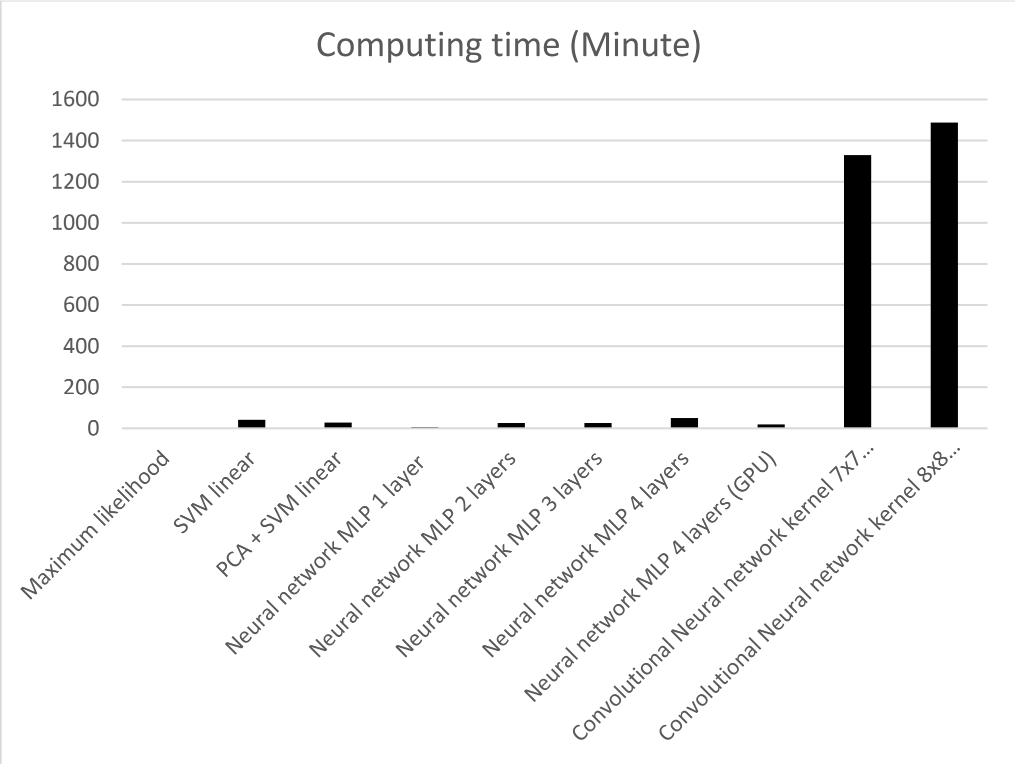

Figure 5 The comparison of the computing times of land cover classification methods

The comparison of the precision in each class of land cover classification methods demonstrates in table 2. The bar graph in figure 6 shows the precision in each class of land cover classification methods.

Table 2 The comparison of the precision in each class of land cover classification methods

No	Method	Urban	Paddy	Maize	Cassava	Sugarcane	Rubber	Oil palm	Forest	Water
1	Maximum likelihood	0.65	0.46	0.07	0.22	0.44	0.16	0.09	0.95	0.82
2	SVM linear	0.77	0.66	0.05	0.61	0.76	0.64	0.17	0.89	0.97
3	PCA + SVM linear	0.84	0.66	0.02	0.69	0.68	0.71	0.03	0.88	0.97
4	Neural network MLP 1 layer	0.85	0.76	0.56	0.77	0.77	0.73	0.74	0.91	0.97
5	Neural network MLP 2 layers	0.87	0.78	0.33	0.78	0.77	0.67	0.76	0.93	0.95
6	Neural network MLP 3 layers	0.84	0.81	0.37	0.68	0.85	0.84	0.76	0.92	0.98
7	Neural network MLP 4 layers	0.90	0.77	0.56	0.76	0.77	0.77	0.79	0.94	0.98
8	Neural network MLP 4 layers (GPU)	0.88	0.77	0.00	0.72	0.63	0.74	0.68	0.92	0.98
9	Convolutional Neural network input 7x7 (GPU)	0.94	0.91	0.45	0.81	0.69	0.87	0.88	0.98	0.98
10	Convolutional Neural network input 8x8 (GPU)	0.94	0.91	0.5	0.84	0.75	0.9	0.91	0.98	0.98

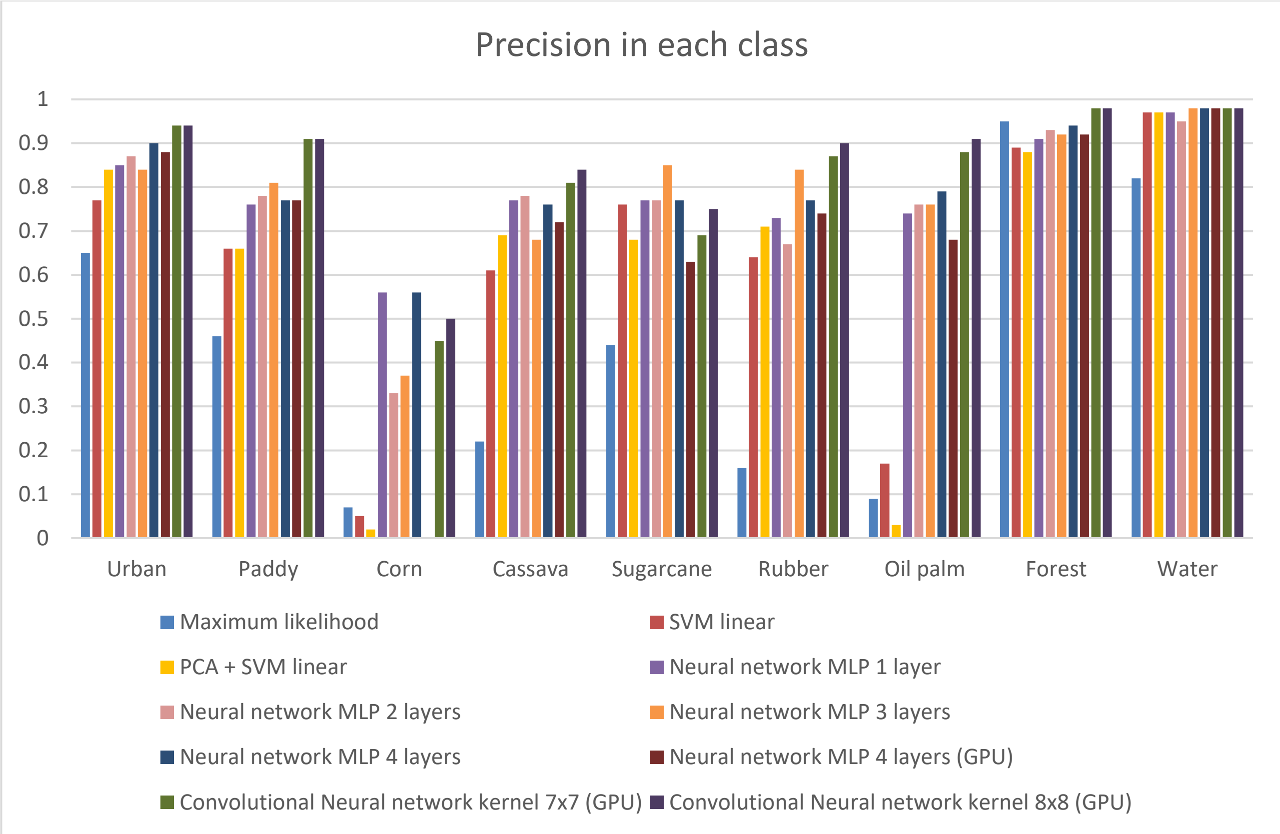

Figure 6 The comparison of the precision in each class of land cover classification methods

The confusion matrix of land cover classification method by using (1) maxim likelihood shows in table 3. The confusion matrix of land cover classification method by using (7) neural network using multi-layer perceptron with 4 hidden layers composed of 100 nodes in each hidden layer shows in table 4.

Table 3 The confusion matrix of land cover classification method by using maxim likelihood

		Predicted class								
		Urban	Paddy	maize	Cassava	Sugarcane	Rubber	Oil palm	Forest	Water
True class	Urban	253345	21909	705	36147	755	16765	1949	29906	10282
	Paddy	13602	138032	3300	16504	96935	112536	40587	97189	309
	maize	406	2348	11521	8405	2517	22774	2494	1390	0
	Cassava	9231	6280	37352	61303	2765	55503	3804	5117	59
	Sugarcane	2386	33225	1675	4877	129225	30586	23467	22772	96
	Rubber	3832	27460	24288	44796	43915	636579	88849	175906	108
	Oil palm	424	2115	621	1198	620	55094	179243	54722	59
	Forest	86747	69692	79166	98991	18031	2979436	1600141	7750878	106547
	Water	19951	1090	26	458	52	883	306	30156	551472

Table 4 The confusion matrix of land cover classification method by using convolution neural networks with input 8x8 pixels by using GPU

		Predicted class								
		Urban	Paddy	maize	Cassava	Sugarcane	Rubber	Oil palm	Forest	Water
True class	Urban	355504	4523	26	663	913	868	400	4618	4318
	Paddy	7822	450057	1061	27479	5793	4995	2247	17434	1765
	maize	508	3671	6256	1985	18027	6259	814	14136	48
	Cassava	1123	14972	345	219380	8007	1275	412	2917	271
	Sugarcane	1538	3791	2142	5001	150442	8546	1119	8640	303
	Rubber	1544	4251	1037	1125	7955	904858	8603	114894	381
	Oil palm	787	3132	160	742	982	11748	253114	23213	182
	Forest	7360	9971	1500	3461	6951	62478	11138	12681756	6021
	Water	3540	1524	27	266	529	226	59	7802	590456

3.2 Discussions

From the experimental results as table 1-4 and figure 3-6, we investigated that the land cover classification using (1) maxim likelihood gave the lowest overall accuracy (the overall accuracy of 60.29%) but it took the fastest computing time (the computing time of 35 seconds).

While the land cover classification using (2) support vector machine using linear kernel provided a high accuracy (an overall accuracy of 87.10%) but it gave a low value of the precision in each class especially; the class of maize (accuracy of 5%). Also, it took a slow computing time (the computing time of 43 minutes).

Then, the land cover classification using (3) support vector machine using the linear kernel, and principal component analysis did not give a higher overall accuracy (an overall accuracy of 86.96%) than using support vector machine using linear kernel but it took the faster computing time (computing time of 28 minutes).

Next, the land cover classification using (4) neural network using multi-layer perceptron with 1 hidden layer composed of 100 nodes provided a high accuracy (an overall accuracy of 89.56%) and gave the acceptable value of the precision in each class. Also, it took the fast computing time (computing time of 7 minutes).

Then, we found that when the number of hidden layer increases, the accuracy will be higher such as the land cover classifications using (5) neural network using multi-layer perceptron with 2 hidden layer composed of 100 nodes in each hidden layer, (6) neural network using multi-layer perceptron with 3 hidden layers composed of 100 nodes in each hidden layer but it takes the slower computing time.

Here, the land cover classification using (7) neural network using multi-layer perceptron with 4 hidden layers composed of 100 nodes in each hidden layer gave the high accuracy (overall accuracy of 91.83%).

when the graphics processing unit was employed such as the land cover classifications using (8) neural network using multi-layer perceptron with 4 hidden layers composed of 100 nodes in each hidden layer, it took the faster computing processing time (computing time of 21 minutes). However, we found that accuracy was reduced (overall accuracy of 90.16%) since it may be incorrect in setting the parameters.

Then, the land cover classification using (9) convolution neural networks with input 7x7 pixels by using GPU provided a very high accuracy (the overall accuracy of 96.38%). It provided very high accuracy in each class But, it took the very slow computing time (the computing time of 22 hours 9 minutes.).

Finally, we investigated that land cover classification using (10) convolution neural networks with input 8x8 pixels by using GPU gave the highest accuracy (overall accuracy of 96.93%). It provided a very high accuracy in each class such as the three highest ranks including water (an accuracy of 98%), forest (an accuracy of 98%), urban (an accuracy of 94%) and the three lowest ranks including maize (an accuracy of 50%), sugarcane (an accuracy of 75%), cassava (an accuracy of 84%). However, it took the slowest computing time (the computing time of 24 hours 48 minutes).

4. CONCLUSION

We developed land cover classification method using convolution neural networks for the economic crop in Thailand using Landsat-8 multispectral images. In the experimental results, our proposed method based on convolutional neural networks gave successfully a prominent classification accuracy of 97% with Kappa coefficient of 0.91. While, the other methods provided accuracies and Kappa coefficients of 60% and 0.31 for Maximum likelihood, 87% and 0.57 for Support vector machine, and 92% and 0.76 for Multilayer perceptron neural networks. Nevertheless, it made the slower computing time than the other methods.

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