AUTOMATIC DETECTION OF SEA FARMS USING ANN

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ABSTRACT : The South Korean government has manually surveyed the actual production of the local aquaculture marine products each year by using aerial photographs or satellite images in order to stabilize the supply of the products in the market(KMI, 2014). However, the manual surveys on various sea farms require an enormous amount of time and labor. In order to address these problems and automatically detect sea farms from high-resolution satellite images from satellites (e.g., KOMPSAT-3), a method that uses machine learning (e.g., artificial neural network [ANN]) has been suggested in this study. First, the classes, which are going to be detected from the KOMPSAT-3 satellite images of sea farms for learning, are defined. The 1,500-pixel coordinates from each class are randomly selected, and the DN values of the pixels are extracted. Various vegetation indexes (e.g., NDVI) are generated by using the DN values, while the feature data are generated by combining the DN values and various indexes. ANN is learned by using the feature data of each pixel and the defined class numbers. When question images are entered into the learned ANN, it outputs classes by pixel. Raster data, which can estimate the sea farms, could be obtained from the binary images outputted by class via post-processing, such as labeling.

1. INTRODUCTION

For the stable supply of aquaculture marine products in the market, the Korean government has manually investigated the actual production of domestic aquaculture marine products every year by using aerial photographs or satellite images. This means that a person can check all the images, as well as detect the location and quantity of sea farms. However, an enormous amount of time and labor are required in order to manually examine various sea farms. In order to resolve this problem, a method for the automatic detection of sea farm objects from high-resolution satellite images (e.g., KOMPSAT-3) by using an artificial neural network (ANN) was proposed in the current study(K.R., 1958, D.E., *et al.* 1986). First, a classifier needs to be trained, and many groups are collected by allocating each band of satellite image and DN value of each vegetation index to a single group, based on the same coordinates. Then, the object class is defined for each group by using indicative data. The data, where the object class has been defined, are trained by using ANN. When a satellite image for the detection of sea farms is entered, the classifier collects each band data of the satellite image and data for each vegetation index, based on the pixel coordinates, and the object class for each pixel of the image is obtained by entering the data into the trained classifier. The obtained data is a raster image data, while the object is obtained via labeling and post-processing(Rosenfeld A. *et al.* 1996).

2. SATELLITE IMAGE

For the detection of the number and location of sea farms, the Korean government has used aerial photographs or satellite images every year. In this study, sea farm objects were detected by using the KOMPSAT-3 satellite images, which have a lower resolution, as compared to aerial photographs. However, it has a 0.7-m level; therefore, the identification of sea farms is possible. In the case of aerial photographs, shooting is limited depending on the flight condition of an aircraft, and an enormous amount of cost and time are needed for the operation of an aircraft, thereby resulting in limited shooting. In the case of satellite images, shooting is enabled at a relatively lower cost, as compared to aerial photographs, and the image of a specific location can be shot periodically, since a satellite revisits a specific location on certain occasions. In addition, the channels of KOMPSAT-3 include Near Infrared Ray (NIR), along with Blue (B), Green (G), and Red (R), and various vegetation indices (e.g., NDWI and NDVI) can be calculated (Macfeeters, 1996). This enables easy object identification, and increases the dimensionality of the feature for each object that can be read from an image, which is more advantageous for a machine learning model (e.g., ANN). Wando, which is a region in Korea with an active aquaculture industry, has been selected as the area to be used in the study.

3. FEATURE EXTRACTION

In order to train ANN, features were extracted from the image. The feature data used in the study were organized as follows.

Table 1. Image features used in the study

Number	Name	Explanation
1	$Blue$	Blue, Band 1 of KOMPSAT-3
2	$Green$	Green, Band 2 of KOMPSAT-3
3	Red	Red, Band 3 of KOMPSAT-3
4	NIR	Near Infrared Ray, Band 4 of KOMPSAT-3
5	$NDWI$	Water index, $(Green-NIR)/(Green+NIR)$
6	$NDVI$	Vegetation index, $(NIR-Red)/(NIR+Red)$
7	$B-NDVI$	Index using Blue and Near Infrared Ray, $(NIR-Blue)/(NIR+Blue)$
8	$NDVI^2$	Square of $NDVI$

Table 1 summarizes the image features that were used in the study. Numbers 1, 2, 3, and 4 in Table 1 are the data that can be directly obtained from the KOMPSAT-3 image. Number 5 is the water index (NDWI), and it can be calculated by using Green and Near Infrared Ray. Number 6 is the vegetation index (NDVI), and it can be calculated by using Red and Near Infrared Ray. Number 7 is the index using Blue and Near Infrared Ray, and it can be calculated by using Blue and Near Infrared Ray. Number 8 is the index obtained by the square of NDVI, and it is calculated by NDVI squared.

4. ANN CLASSIFIER LEARNING

ANN is an algorithm that has been made based on the structure of the neuron of a living organism, and it is divided into the input layer, hidden layer, and output layer, as shown in Figure 1. The data of each layer node is delivered, as shown in Figure 2. The required number of nodes for the input layer is identical to the number of feature data. The data of the input layer node was delivered to the hidden layer, while the nodes of the hidden layer performed the calculation by assigning each different weighting factor to the values delivered from the input layer. In this study, the number of nodes for the input layer was set to 8, which was identical to the number of features. The number of nodes for the hidden layer was set to 24. The number of nodes for the output layer was set to 5, which was identical to the number of object classes.

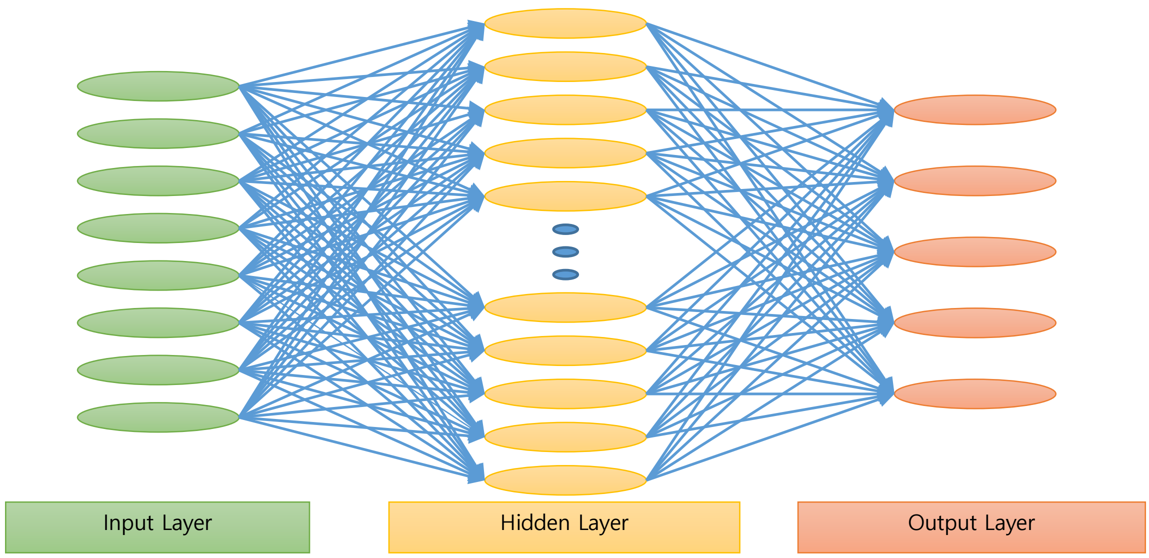

Figure 1. Structure of the artificial neural network (ANN) used in the study

For the training, the indicative data was made, as shown in Figure 2.

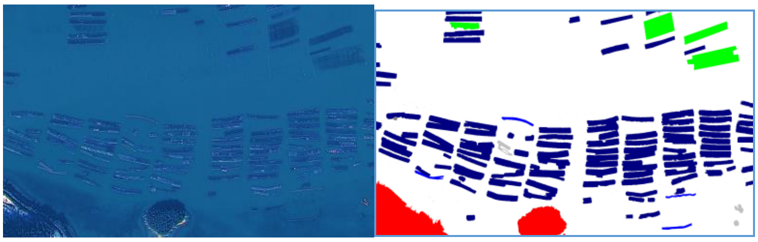

Figure 2. Indicative data

The program used in this study was developed, so that it could read the actual coordinates and image size of the indicative data in Figure 2. Moreover, it could read the satellite image by automatically fitting the coordinates and sizes. The color of the indicative data represents the classification of the object class.

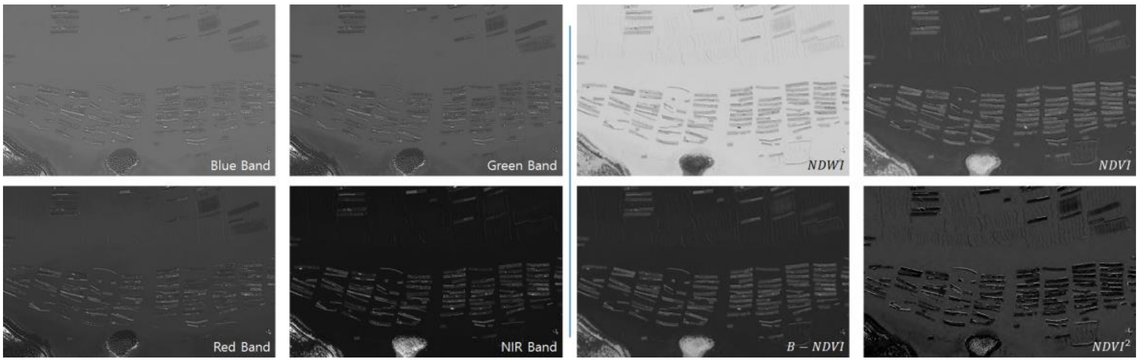

Figure 3. Images of each band for the KOMPSAT-3 satellite image (left) and images that combined each band (right)

The data shown in Figure 3 are collected as feature data, based on the same pixel coordinates. The data at the same coordinates of the indicative data indicates the object class. This corresponds to the class column of the table shown in Figure 4.

B	G	R	IR	NDWI	NDVI	B-NDVI	NDVI^2	Class
0.551407	0.467264	0.378706	0.329200	0.586673	0.465034	0.373834	0.004891	3
0.156276	0.123879	0.070637	0.000000	1.000000	0.000000	0.000000	1.000000	3
0.386577	0.300734	0.189482	0.054150	0.847415	0.222261	0.122865	0.308556	3
0.454845	0.366477	0.303429	0.219130	0.625807	0.419340	0.325131	0.026024	3
0.442507	0.351807	0.251611	0.103239	0.773124	0.290937	0.189170	0.174830	0
0.339694	0.252377	0.179943	0.069585	0.783872	0.278866	0.170019	0.195601	3
0.467511	0.386308	0.327404	0.277581	0.581887	0.458823	0.372546	0.006782	3
0.198388	0.153491	0.092034	0.000000	1.000000	0.000000	0.000000	1.000000	3
0.421944	0.341483	0.234597	0.105263	0.764378	0.309725	0.199662	0.144818	0
0.467018	0.377886	0.278938	0.171053	0.688394	0.380125	0.268078	0.057480	3
0.367988	0.279272	0.196185	0.091093	0.754045	0.317091	0.198425	0.133823	3
0.401217	0.306167	0.229441	0.154858	0.664100	0.402963	0.278484	0.037665	3
0.316499	0.258354	0.199536	0.094130	0.732953	0.320533	0.229233	0.128833	3
0.414871	0.327357	0.239237	0.158401	0.673910	0.398355	0.276310	0.041327	3
0.532160	0.406955	0.305233	0.260881	0.609364	0.460827	0.328962	0.006138	3

Figure 4. Examples of feature data

In this study, the data were collected, as shown in Figure 4. In order to match the quantity, the data collection was performed by selecting a random position for each object class from all the pixels.

5. SEA FARM OBJECT DETECTION AND LABELING

The objects were extracted from a random region by using the trained ANN, as shown in Figure 7. The legend of the object recognition result image is summarized in Table 2.

Table 2. Legend of the raster result image

Color	RGB value	Explanation
Yellow	255, 255, 0	Land detected by NDWI
Dark blue	0, 85, 0	Land
Brown	85, 0, 0	Sea
Light blue	0, 255, 255	Cage-type sea farm
Red-violet	255, 0, 255	Longline-type sea farm
Dark green	0, 85, 0	Others

The image entered was the sea farm region near Wando at the southern coast of Korea, and the coordinates are 162005.9 and 173317.2. The coordinate system is WGS 84 / UTM zone 52N.
For the data of each object class detection result, as shown in Figure 7, labeling was performed for each object class. In this regard, the image can be organized, so that only significant objects are left based on the number of pixels for each object.

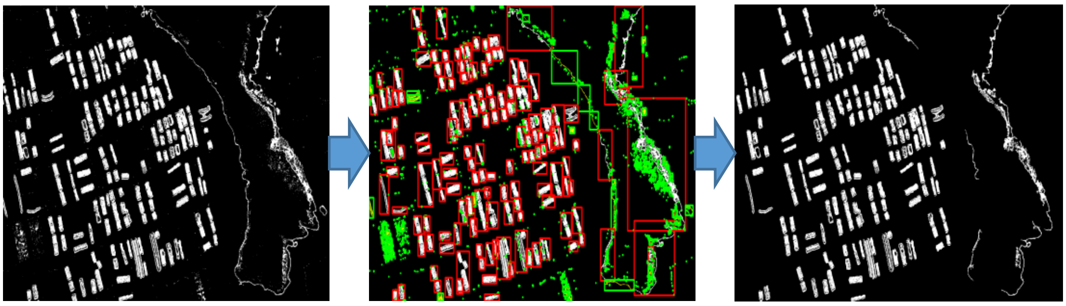

Figure 5. Labeling for the cage-type sea farm

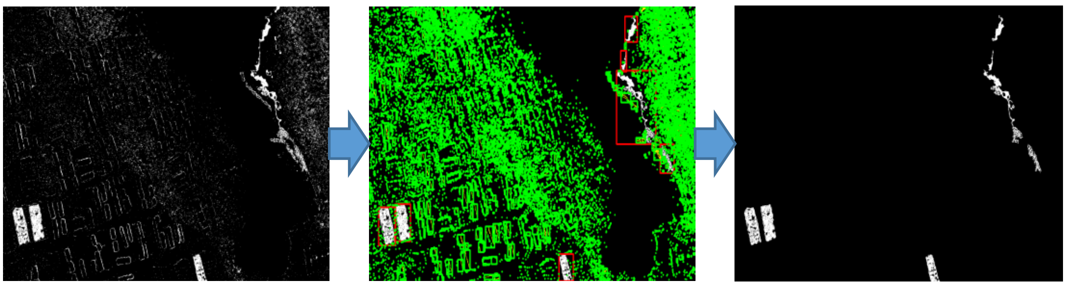

Figure 6. Labeling for the longline-type sea farm

In Figure 5, the number of pixels for each object can be examined, based on the labeling, thereby resulting in only significant parts, which can be filtered based on the quantity. However, the region, which misdiagnosed the land area, needs improvement.
In Figure 6, a lot of noise could be eliminated, based on the labeling.

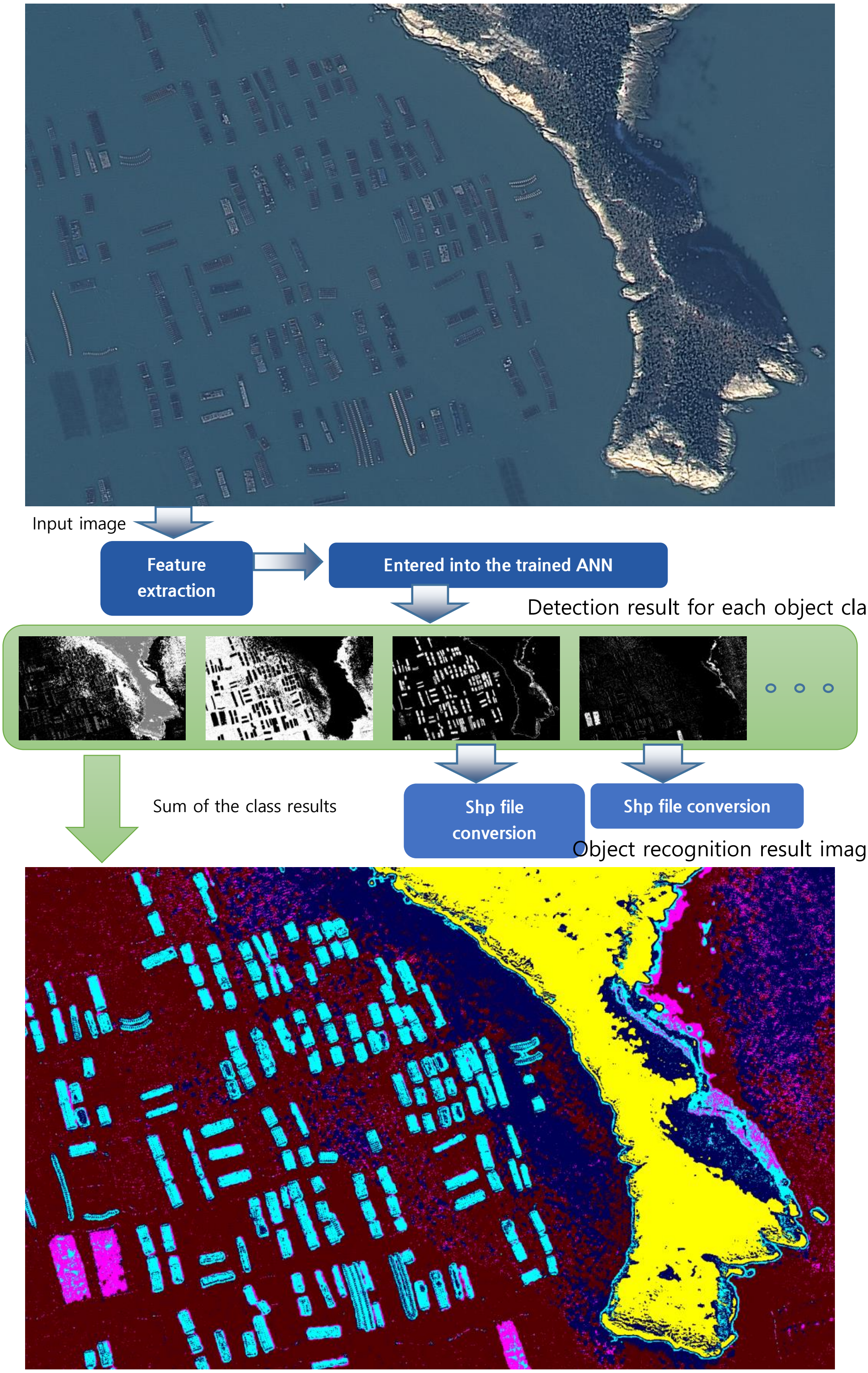

Figure 7. Procedures for the image input and the raster data output of the sea farm detection result

6. CONCLUSION

In this study, a method for the recognition of sea farm objects from the KOMPSAT-3 satellite image by using ANN was proposed. ANN was trained by extracting the features for each class, while the class for each pixel was recognized from the image entered by using the trained ANN. The result could be obtained by eliminating the noise through labeling. As for the future research projects, a machine learning method other than ANN can be applied, and the object recognition performance can be improved by diversifying the features.

7. ACKNOWLEDGEMENT

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