Exploration of the Earth Environment using "Himawari-8" data of Meteorological Satellite and Deep Learning

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ABSTRACT

In the field of satellite remote sensing, artificial intelligence (AI) is the method frequently used to explore the global environment in many researches. Deep learning is widely used to analyze the satellite images. The detection or tracking on typhoons, clouds, land and snow are examples of research on the earth's environment with deep learning. The conventional method, RGB and IR images of the satellites, are used as the inputs of deep learning using convolution operations such as convolution neural networks (CNN). We have developed the method to investigate the earth's environment and its variations. The method is based on the supervised learning model of artificial intelligence with 16 wavelength spectral image data (from visible to infrared range) obtained by the geostationary meteorological satellite "Himawari-8". The input layer was given information of 16 wavelengths instead of an image, not convolution operation. The output from the proposed algorithm is classification of 6 classes such as typhoon, cloud, sea, land, snow and ice. We also succeeded in visualizing that typhoons and developed clouds contain snow and ice. The combination of spectrum data acquired by satellites and our proposed method is effective for forecasting typhoons, and drift ice, torrential rain and so on. By providing spectral data of the meteorological satellite "Himawari-8" to the input layer of the proposed method, our model can recognize the earth environment in all space and time (365 days, 24 hours). The model developed this time has reached the accuracy of 96.5%. It will be an effective method for drawing out the capabilities of artificial satellites in the environment exploration of the earth and planets.

Keywords: Himawari-8, 16-wavelengths, Artificial Intelligence, Deep Learning, Supervised Learning

1. INTRODUCTION

Surveys of the global environment have helped human lives. Artificial intelligence has been applied widely in the field of remote sensing. In addition, CNN (Convolutional Neural Network) is the most commonly used technique to analyze the remote sensing data. According to the studied results in [1], convolutional neural network is used to analyze global environmental changes (i,e, Typhoon, Cloud, etc.), and Himawari-8 infrared images (Bands 8, 10 and 14) were developed, and a network that recognizes typhoons by binary classification was developed, and a network that identifies the typhoon from the recognized typhoon at the center of the typhoon was also developed. Additionally, the CAM (Class Activation Map) [2] is also employed to visualize the inside of the typhoon image to understand the characteristics of the typhoon.

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Another approach is to use cloud detection using multispectral images [3] and satellite image data (visible in the infrared) and provide them to the input layer of a neural network [4]. In addition to cloud detection, there are also network reports that classify and identify multiple global environments. In [5], a deep convolutional network was proposed that distinguished cloud and snow at the pixel level using multiscale prediction. In multi-scale learning (such as ensemble learning), low-level spatial information and high-level semantic information are used at the same time, resulting in highly accurate recognition results. In general, CNN focuses on the shape of the process that performs the convolution operation. Therefore, the perception of spatial information tends to be weak. However, spatial awareness can be overcome by using data extensions on the dataset or by using pixel-aware segmentation. Exploration reports of the global environment using artificial intelligence include not only clouds but also land cover. In [6], high-resolution remote sensing images and convolutional networks were used for urban and land cover detection and classification. As a result, successfully detected and classified trees, grass, roads, water, etc.

Many reports have attempted to detect clouds. Furthermore, in the field of exploring the earth's environment, there have been reports that not only analyzed satellite data with deep learning but also succeeded in identifying various types of clouds using ground-based cloud data [7]. It labeled artificial intelligence teacher data with the eyes of meteorological experts. Therefore, preprocessing for artificial intelligence to learn global environmental changes having complicated characteristics requires the eyes of experts in the field. Currently, labeling supervised data in supervised learning of the earth's environment in the field of remote sensing is very labor intensive and time consuming, and this problem has not been solved.

Applying big data to convolutional neural networks is expected to have high results, but it is computationally expensive. On the other hand, there is a report that investigates the earth's environment using an ANN that does not require a CNN [8]. These are most relevant to the method of our study. In the study of [8], in order to investigate the precipitation characteristics, the brightness temperature difference (BTD) and the reflectance (Ref) derived from the new Advanced Baseline Imager (ABI) onboard the GOES-16 satellite were used as features. A DNN (Deep Neural Network) was proposed to detect daytime rain clouds and non-rain clouds and delineate the convective area. This automatic cloud classification system showed excellent performance that can be expected for detecting extreme rain events and real-time prediction (obtaining data every 5 minutes). ANN has low computational costs and can quickly respond to earth's environmental changes.

In summary, in the field of earth science, various AI (Models) are being built and developed with tremendous speed in order to set global environmental change. CNN and ANN using satellite data are in a trade-off relationship. A CNN that features satellite image data focuses on shape and is strong on land with less complexity than the atmosphere (land cover problem). On the other hand, ANNs with features such as reflectance and brightness temperature can detect and recognize complex clouds, but they are inferior to CNNs in learning shapes.

In this research, we develop a neural network related to ANN and propose an algorithm that can recognize both atmospheric clouds and land areas.

The remaining part of this paper is organized as follows. In section 2, introduces proposed methodology. In section 3, introduces our model's result and discussion. In section 4, introduces Conclusion.

2. MATERIALS AND METHODS

2.1 Earth environment data

The geostationary meteorological satellite Himawari-8 uses three bands as visible wavelength; band #1 ~ #3, three bands as near infrared wavelength; band #4 ~ #6, and band #7 ~ #16 as infrared wavelength. The data on 16 wavelengths (visible to infrared) are acquired every 2.5 minutes in the vicinity of Japan and every 10 minutes from hemisphere. The spatial resolution directly below the satellite are as: 1 km for band #1, #2 and #4, 0.5 km for band #3, and 2 km for band #5 ~ #16 [9]. Table 1 shows the details of the Himawari8/AHI (Advanced Himawari Imager).

FullDisk data of the geostationary meteorological satellite "Himawari-8" used was downloaded from NICT Science Cloud (WorldScienceDataBank web browser) of National Institute of Information and Communications Technology, and himawari-8 real time web was used to determine the data to download [10].

Table 1. Himawari-8/AHI (Advanced Himawari Imager)

Band Number	**Wavelength (μm)**	**Spatial resolution at Sub satellite point (km)**	**Number of bit per pixel**	**Numbers of pixels**	
				East-West direction	North-South direction
1	0.47	1	11	11,000	11,000
2	0.51	1	11	11,000	11,000
3	0.64	0.5	11	22,000	22,000
4	0.86	2	11	11,000	11,000
5	1.6	2	11	5,500	5,500
6	2.3	2	11	5,500	5,500
7	3.9	2	14	5,500	5,500
8	6.2	2	11	5,500	5,500
9	6.9	2	11	5,500	5,500
10	7.3	2	12	5,500	5,500
11	8.6	2	12	5,500	5,500
12	9.6	2	12	5,500	5,500
13	10.4	2	12	5,500	5,500
14	11.2	2	12	5,500	5,500
15	12.4	2	12	5,500	5,500
16	13.3	2	11	5,500	5,500

The earth environment was classified into six categories: typhoons (developed clouds), sea, clouds, land, drift ice, and snow. An example of these spectral distributions is shown in Figure 1.

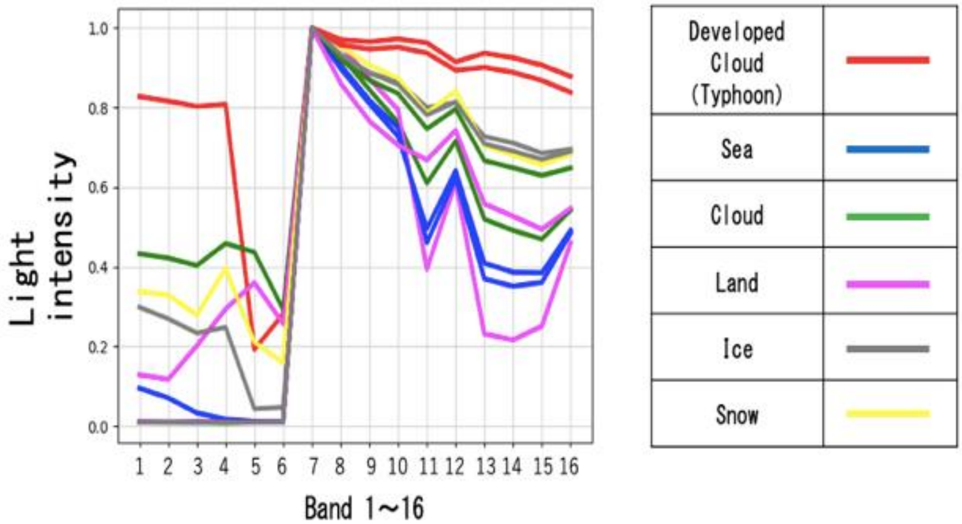


Figure 1 Spectral distributions

The vertical axis is the light intensity normalized by band #7, and the horizontal axis is band #1 ~ #16 of the meteorological satellite "Himawari-8". Each color corresponds to the table on the right. This light intensity spectrum was used as feature value. On the other hand, these features are given to the input layers.

2.2 Proposed Model

In this work we proposed the supervised artificial intelligence model based on neural networks. Figure 2 shows the supervised artificial intelligence model constructed in this study.

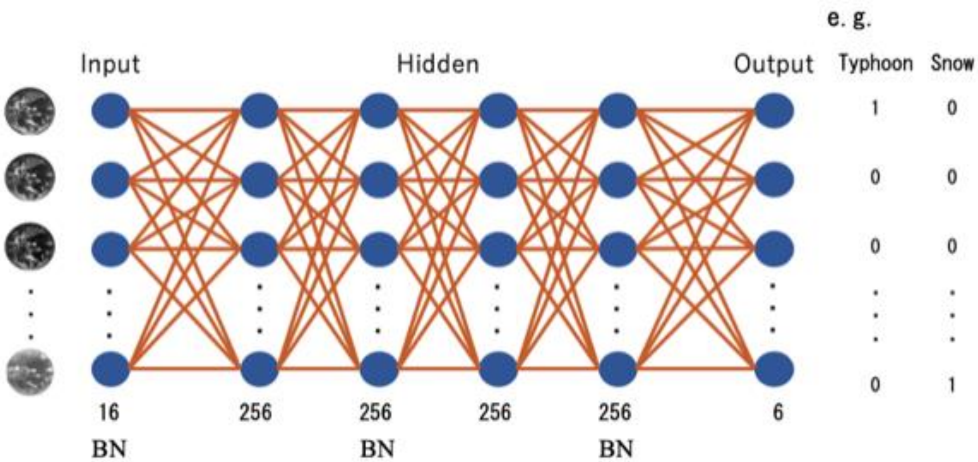


Figure 2 Proposed neural network model

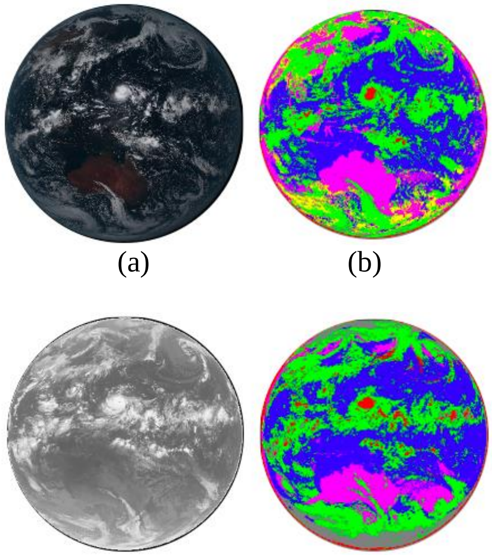
The input layer are spectral data which is extracted from the spectral image data of band #1 ~ #16 (16 wavelengths) of the meteorological satellite "Himawari-8". The spectral data for each pixel is extracted

from the spectral image data, and the extracted 16-wavelength spectral data is given to the input layer. The work of extracting the 16-wavelength spectrum data (determining the true value) in the pre-processing was not automatically extracted. Training data was created one by one, that uses the click function of OpenCV while referring to the True color RGB Composite image. The hidden layer has 256 nodes as 4 layers with fully connected, the activation function used in this work is "Relu".

The output layer corresponds to six earth environments (typhoons (developed clouds), sea, clouds, land, ice and snow). "Softmax" was used as the activation function of the output layer. The softmax function in the output layer exploits the first two highest values for image generation in which it differs from the conventional method. Since the earth environment labeled in the pre-processing was focused on 16 wavelength's information for each pixel instead of the shape (such as CNN), the predicted value closest to the correct label was not only one but two in softmax. The reason for choosing the two softmax predictions is highlighted in the model results in section 3.

3. RESULTS AND DISCUSSION

In this work the sixteen wavelengths from the meteorological satellite Himawari-8 are used. The number of training data is 871and used 10,000 epochs in the learning process. The TensorFlow and Keras are used for modelling artificial intelligence for processing the input data. The training data as the spectrum data was created from data of different seasons and dates such as typhoon, drift ice and snow. The input layer was used batch normalization (BN) [11] and also used in the second fourth layer of the hidden layer. When evaluating the performance of the model, 871 teacher data were divided into 90% training data and 10% test data. To create test data, 10% of teacher data was randomly extracted. As a result of using the weight data created from the training data for the test data, accuracy of the test data is 96.5%. Figure 3 shows the recognized result of "Himawari-8 data" on September 11, 2018, at 12:00 (JST) and 22:00 (JST).



(a) (b)

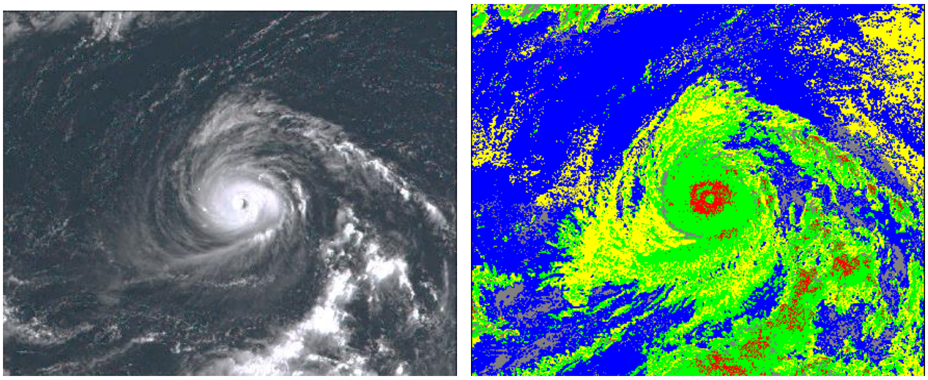
(c) (d)

Figure 3 Comparison test of results, Himawari-8 Full disk data at noon (JST) and 22:00 (JST) in September 11, 2018, (a) True color RGB composite image (b, d) Our model: Test results (c) Band11 image

Figure 3 show the true color RGB image as in Figure 3(a) and the image generated from band #13 as in Figure 3(c), they are created by Python with reference to [12]. The daytime image is shown in Figure 3(a) and nighttime is shown in Figure 3(c). The recognition result from the daytime data and nighttime data are shown in Figures 3(b) and 3(c), respectively. The accuracy of land and so on is ambiguous, but typhoons (developed clouds) can be recognized day and night. The color meaning of the result in Figures 3(c) and 3(d) correspond to the color shown in Figure 1.

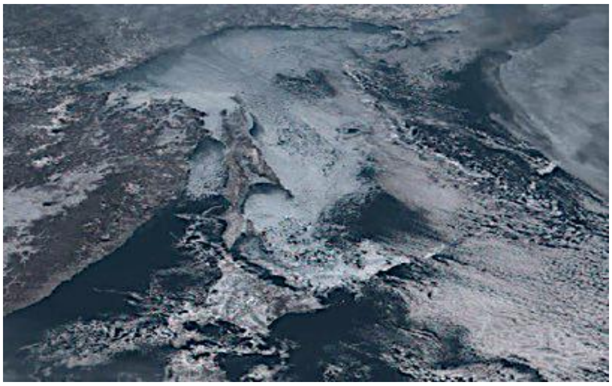
Figure 4 shows the detection of snow and ice in typhoons from Himawari-8 data at 9am (JST) on September 11, 2018 which focuses on the typhoon no.21. The true color RGB composite image is shown in Figures 4(a) and 4(b) is the recognition result from the proposed model. The result shows the sample data which illustrates typhoon no 21 in conjunction with the snow and ice.

The detection of snow and drift ice are shown in Figure 5. The sample data is the data of Hokkaido region (winter) at 12:00 noon (JST) on February 28, 2018. The true color and day Snow-Fog RGB composite image are shown in Figures 5(a) and 5(b), respectively. The day Snow-Fog RGB images are used for comparison because they can distinguish between water clouds and sea ice or drift ice. The sample image in Figures 5(a) and 5(b) are created from the sample data with an image processing program using python with reference to [12-13]. Figure 5c shows the test result from the proposed model. It demonstrates that snow and drift ice are different and they are contained in the cloud, like those in the day Snow-Fog RGB composite images.

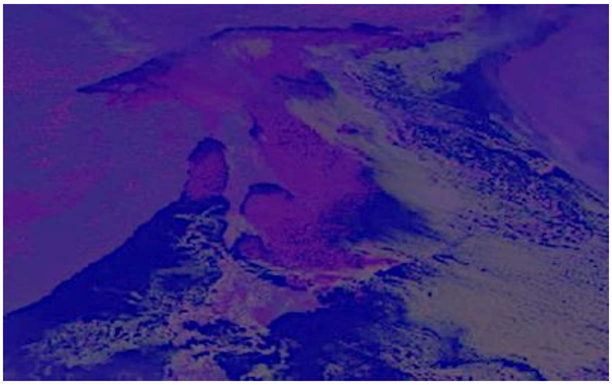


(a) (b)

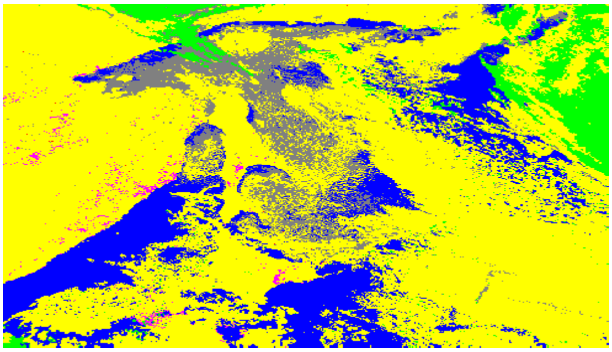
Figure 4 Comparison between the RGB composite image of typhoon No.21 from Himawari-8 data at 9am (JST) on September 1, 2018, and the recognition result. (a) True color RGB composite image (b) Recognition result



(a)



(b)



(c)

Figure 5 Comparison of RGB composite image and our model, Himawari-8 data at Hokkaido region in winter at 12:00 noon on February 28, 2018 (JST) and the recognition result. (a) True color RGB composite image (b) Day Snow-Fog RGB composite image (c) Recognition result

4. CONCLUSIONS

This work is the earth environment exploration by artificial intelligence and geostationary meteorological satellite "Himawari-8" data. This is the first attempt to explore the earth environment using artificial intelligence from 16-wavelength spectral data for each pixel. The spectral data extracted from each pixel of spectral image data captured with 16 wavelengths (visible to infrared) from the meteorological satellite "Himawari-8", then they are used as artificial intelligence input or training data. The spectral data and the earth environment are characterized.

This work proposes the artificial intelligence algorithm to learn, detect and recognize the earth's environment. The input layer was given information of 16 wavelengths instead of an image without convolution operation. The proposed algorithm can be classified into six classes of environmental change such as typhoons, cloud, sea, land, snow and ice. It also succeeded in visualizing that typhoons and developed clouds contain snow and ice. The combination of spectrum data acquired by satellites and the proposed method is effective for recognized typhoons, and drift ice, torrential rain and so on. By providing spectral data of the meteorological satellite "Himawari-8" to the input layer of the proposed method, it can recognize the earth environment in all space and time (365 days, 24 hours) by using hundreds of data sets. The structure of the neural network model has 16 inputs, and the hidden layer has 256 nodes as 4 layers, and 6 outputs. The training data in this model was handcrafted. The model developed this time has reached the accuracy of 96.5%.

Although the earth environment was learned with six types of typhoons, sea, clouds, land, drift ice, and snow, there is also possible to recognize rivers, lakes, land, mountains, forests, and various clouds. However, it is extremely difficult to manually label the earth's environment area well. By reason, it is necessary to develop an unsupervised learning model in next work.

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