Information Modelling and Knowledge Bases XXXIV
M. Tropmann-Frick et al. (Eds.)

doi:10.3233/FAIA220489

AI-Sensing Functions with SPA-Based 5D World Map System for Ocean Plastic Garbage Detection and Reduction

Yasushi KIYOKI[a,1] Shiori SASAKI[b] Ali Ridho Barakbah[c]

[a,b] *Keio University, Japan and Musashino University, Japan*
[c] *Politeknik Elektronika Negeri Surabaya, Indonesia*

Abstract. The "SPA-based 5D World Map System" realizes Cyber-Physical-Space integration to detect changes of environmental phenomena with real data resources in a physical-space (real space), map them to the cyber-space to make knowledge bases and analytical computing, and actuate the computed results to the real space with visualization for expressing the causalities and influences. This paper presents an important application of 5D World Map System, adding "AI-Sensing" functions for "Global Environment-Analysis" to make appropriate and urgent solutions to global and local environmental phenomena in terms of short and long-term changes. Focusing on the ocean plastic garbage issues, this paper describes the methodology of AI-Sensing, the preliminary models and experiments on the accuracy of AI-Sensing and the substantiative experiments on the feasibility and effectiveness of AI-Sensing with real local data. In addition, the example outputs of the integration of AI-Sensing algorithm and SPA-based 5D World Map System and the future direction of a collaborative project for ocean plastic-garbage reduction are introduced.

Keywords. CPS, Cyber-Physical-System, Sensing-Processing-Actuation, Machine Learning, Image, Visualization, Knowledge, SDGs, SDG14, Marine Pollution, Ocean Environment, City, River, Coastal waste, Global Environment

1. Introduction

"SPA-based 5D World Map System" [5]-[11] is a global and environmental knowledge-integrating and processing system for memorizing, searching, analyzing and visualizing "Global and Environmental Knowledge and Information Resources," related to natural phenomena and disasters in global and local environments. This system analyzes environmental situations and phenomena with "environmental multimedia data sharing," as a new global system architecture of collaborative and global environment analysis. This system realizes a remote, interactive and real-time environmental research exchange among different areas.

As an important global environmental system, we have proposed a multi-dimensional data mining and visualization system, 5D World Map System [5]-[11]. The main feature of this system is to realize semantic data mining, visualization and analysis in the "multi-dimensional semantic space" and "semantic-distance computing" with

[1] Yasushi Kiyoki, Corresponding author, Keio University, Endo 5322, Fujisawa, Kanagawa, Japan; E-mail: kiyoki@sfc.keio.ac.jp.

semantic functions. This space is created for dynamically computing semantic equivalence, similarity and difference as distance functions.

In this paper, we present an important application of 5D World Map System, adding AI-Sensing functions for "Global Environment-Analysis" to make appropriate and urgent solutions to global and local environmental phenomena in terms of short and long-term changes. The following "six functional-pillars" are essentially important with "environmental knowledge base creation" for sharing, analyzing and visualizing various environmental phenomena and changes in the real world.

1) Cyber & Physical Space Integration
2) SPA-function
3) Spatiotemporal computing
4) Semantic computing
5) World map-based visualization
6) Warning message propagation

The "SPA-based 5D World Map System" realizes Cyber-Physical-Space integration to detect changes of environmental phenomena with real data resources in a physical-space (real space), map them to the cyber-space to make knowledge bases and analytical computing, and actuate the computed results to the real space with visualization for expressing the causalities and influences. The 5D World Map System and its applications create new analytical circumstance with the SPA concept (Sensing, Processing and Analytical Actuation) for sharing, analyzing and visualizing natural and social environmental aspects. This system realizes "environmental analysis and situation-recognition," which will be essential for finding out solutions for global environmental issues.

To enhance SPA functions, we have developed a sensing algorithm called "AI-Sensing" to analyze photos and images captured by mobile phones, cameras and other instruments on the ground and from aerial devices (such as drones) to detect specified objects such as plastic garbage on the water surface. AI-Sensing algorithms are based on intelligent sensing with machine learning and deep learning, including image-filtering process with "domain-boundary" analysis for color, shape, and location variables. The main feature of the methodology of AI-Sensing is the analyzing function for multiple patterns of plastic waste pollution scenarios based on heterogeneous data resources such as images, texts, statistics, sound, and video. When the users set up conditions and query, the algorithm will evaluate all the connected image data, by means of spatial, temporal and semantic computation functions, and integrate these results of dynamic multi-contextual computation onto a set of chronologically-ordered maps of 5D World Map System.

This paper consists of 7 sections. In Section 2, the overview of SPA-based 5D World Map System with AI-Sensing functions for UN-ESCAP Closing the Loop project on the ocean plastic monitoring [12] is introduced. In Section 3, the methodology of AI-Sensing is explained. In Section 4, the preliminary model and experiments on the accuracy of image sensing algorithms are described. In Section 5, the substantiative experiments on the feasibility and effectiveness with real local data are described. In Section 6, the example outputs of the integration of AI-Sensing algorithm and 5D World Map System are introduced.

2. Overview of SPA-based 5D World Map System and UN-ESCAP Closing-the-Loop project

5D World Map System [5]-[11] is a knowledge representation system that enables semantic, temporal and spatial analysis of multimedia data and integrates the analyzed results as 5-dimentional dynamic historical atlas (5D World Map). The composition elements of 5D World Map are a spatial dimension (3D), a temporal dimension (4D) and a semantic dimension (5D).

A semantic associative search method [1][2][3] is applied to this system for realizing the concept that "semantics" of words, documents, multimedia, events and phenomena vary according to the "context". The semantics of each target multimedia data regarding to any events, phenomena or topics are calculated on a multidimensional vector space and represented as one dimensional ranking on a time-series world map space. The main feature of this system is to create various context-dependent patterns of social stories according to user's viewpoints and the diversity of context in phenomena dynamically.

As an important global environmental system, we have proposed 5D World Map System [5]-[11] as a multi-dimensional data mining and visualization system. In the design of this global environment-analysis system, we focus on methodology for searching and analyzing environmental media data related to environmental situations and phenomena. This system realizes semantic computing and search for media data and it is applied to compute semantic correlations between keywords, images, sensing data, sound data, documents and sensing data dynamically, according to user's contexts and analysis-points in a context-dependent way. The main feature of this system is to realize semantic computing in the multi-dimensional semantic space with semantic distance functions. This space is created for dynamically computing semantic equivalence, similarity and difference as distance functions.

5D World Map System [5]-[11] has been providing various functionalities to share and visualize various types of multimedia data [6][7][8]. A combination of the analysis and visualization functions for multimedia and real-time sensing-data of 5D World Map System has been proposed to make environmental analysis much richer and deeper, which contributes to activities of collaborative environmental knowledge creation. Also, a multi-dimensional and multi-layered visualization and Monitoring-Analysis-Warning functions of 5D World Map System for building sustainable ocean and disaster resilience has been proposed for monitoring Sustainable Development Goals (SDG14, SDG9, SDG11) in United Nations ESCAP [9][10][11].

Currently, the 5D World Map System is globally utilized as a Global Environmental Semantic Computing System, in SDG14, UN ESCAP's Closing the Loop project [12] for observing ocean-environment situations with local and global multimedia data resources [9][10]. The objective of Closing-The-Loop project is to monitor and reduce the environmental impact of four cities in ASEAN (Da Nang, Viet Nam; Kuala Lumpur, Malaysia; Surabaya, Indonesia; Nakhon Si Thammarat, Thailand) by tackling plastic pollution. In this project, we include new functions of AI-Sensing to 5D World Map System and apply the analytical visualization functions in the SPA (Sensing-Processing-Actuation) process to detect the location, date/time and the amount of serious plastic pollution in the cities as shown in **Figure 1**.

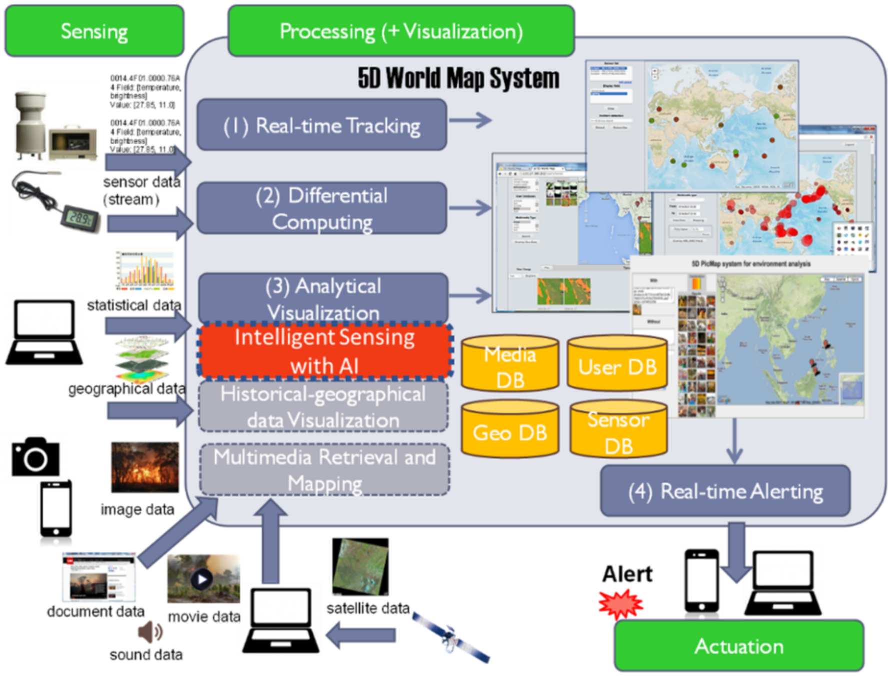


Figure 1. System Structure of SPA-based 5D World Map System with AI-Sensing

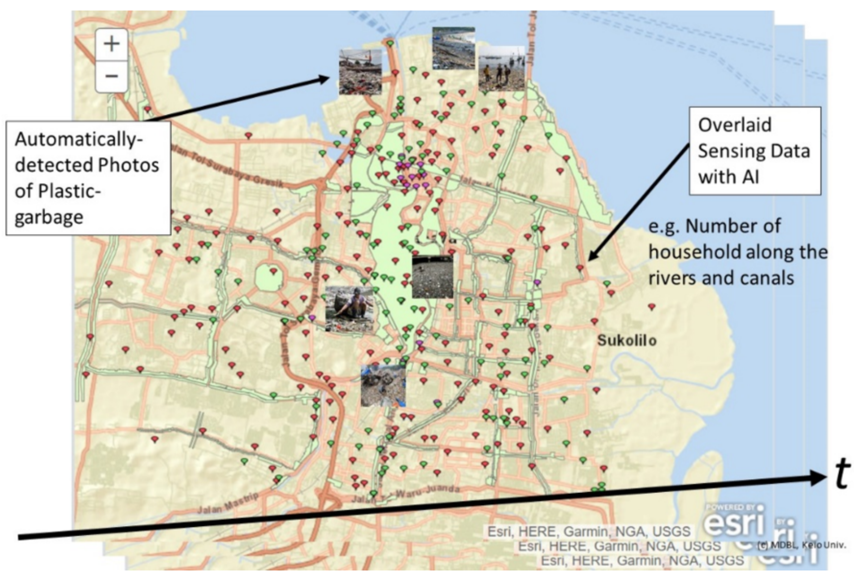


Figure 2. Output Image of SPA-based 5D World Map System with AI-Sensing module: Surabaya Case (photos + demographic data)

Figure 2 shows the output image of 5D World Map System with AI-Sensing module using plastic garbage photos, demographical data and water-quality sensing data in Surabaya, Indonesia. If a user (a local resident) takes some photos of plastic garbage in the city, canals, rivers and coastal areas and upload to the 5D World Map System, then the AI-Sensing module judges whether the photos include plastic garbage or not, how match the garbage is included, where and when the photos are taken, and the photos are mapped to the time-series maps automatically. Also, if another user (a researcher) uploads the demographical data such as the number of houses in the city with geolocation or the sensing data such as water quality of canals and river, the system also visualize the statistical and numerical data together with the uploaded image data.

3. AI-Sensing

3.1. 3-Phase Algorithm for "AI-Sensing"

A 3-Phase Algorithm has been designed as an Intelligent Sensing AI process for plastic garbage detection as shown in **Figure 3** and **Figure 4**. In Phase 1, two sets of images for learning data are collected with "Domain-boundary" such as river/canal/sea image "with plastic-garbage" and "without plastic garbage". In Phase 2, the target image taken by mobile phone, action camera, done or 360-degree camera with Exif is input to the Machine Learning/Deep Learning process as a query to judge if it includes plastic garbage or not. In Phase 3, the judged image with plastic/non-plastic tag is automatically posted and mapped to 5D World Map System.

Phase 1: Image-filtering process with "Domain-boundary" applicable to Deep Learning and Semantic Computing
Phase 2: ML / DL learning for automatic detection of plastic garbage-photos
Phase 3: Automatic posting/mapping of plastic garbage-photos to 5D WMS

Figure 3. 3-Phase Algorithm of AI-Sensing

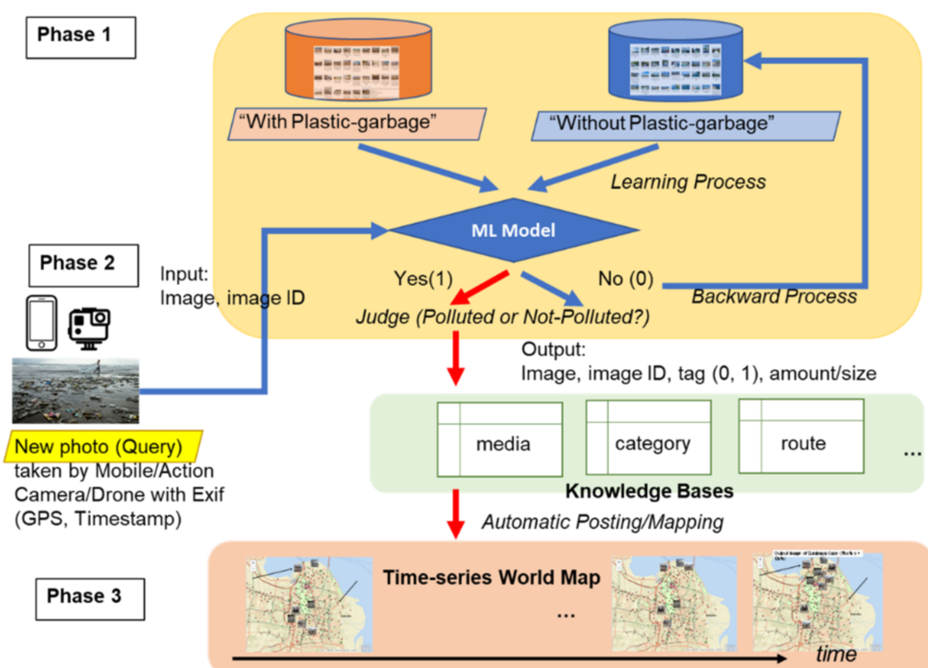


Figure 4. Implementation of AI-Sensing based on the 3-Phase Algorithm in 5D World Map

By this algorithm, it is possible to judge the amount and flow of plastic garbage detected at several spots of monitoring if we set various data sets for learning such as "with plastic", "without plastic", "small amount of plastic", "mid amount of plastic", "big amount of plastic", and so on.

The implementation method is described in **Figure 4**. The Phase-1 and Phase-2 are realized by Java and PostgreSQL and the Phase-3 is realized by PHP interface.

In the Closing the Loop project, 5D World Map System is expected to connect with other external systems such as GIS Data Sharing System (GDSS) developed by Japan Space Systems (JSS) [13] to collect and analyze actual local data as much as possible for the collaborative knowledge base creation and sharing. For the purpose, we have designed an connection method between 5D World Map System and the outer systems as shown in **Figure 5**. Using the integrated two systems, we jointly conducted a series of substantiative experiments for the cases of local cities, which are introduced in Section 5 and Section 6.

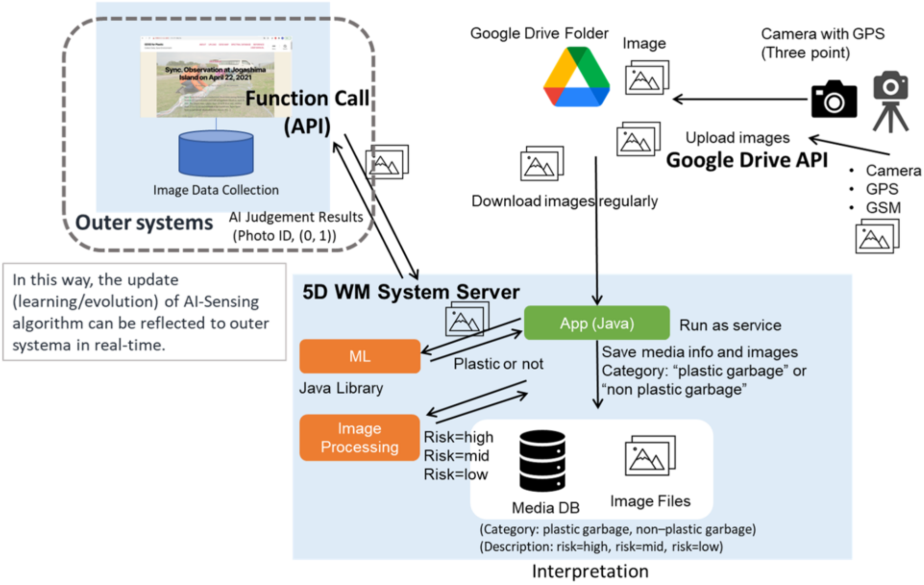


Figure 5. Connection method between 5D World Map System and other external systems

4. AI-Sensing (Model I) and the preliminary experiments for validation

To check the feasibility of AI-Sensing functions, we conducted validation and accuracy tests with a preliminary model (Model I) by machine learning. The general scale of datasets of learning process is defined as follows: a.) less than 100 data, b.) 100 < data < 1,000, c.) 1,000 < data < 10,000, d.) over 10,000 data. In our experiments, we performed accuracy tests of a.), b.) for the first trial and c.) 1,000 < data < 10,000 using online images on the Web.

4.1. Machine Learning Algorithm: Multi perceptron Neural Networks with ALI (Analytical Libraries for Intelligent computing)

To apply Machine Leaning (ML) to the automatic judgement of whether an image include plastic garbage or not and the classification of images with plastic garbage or without plastic garbage, we apply a color feature extraction method with ALI (Analytical Libraries for Intelligent-computing) [4] (**Figure 6**) to our image sensing algorithm and multi perceptron Neural Network (NN) (**Figure** 7) for relatively small data sets (100<data<10000). RGB color information of each image is quantized and converted to 5x5x5 histogram bins of color vectors and the similarity between the images are calculated in the 5x5x5 color vector space.

After color feature extraction, we build the classification model to identify images whether an image inside the river containing plastic garbage, or not. Here we use Multi Perceptron Neural Network consisting of 2-hidden layers with 125 input units (comes from 5x5x5 histogram bins) and 2 output units (comes from 2 classes of plastic garbage and non-plastic garbage). For the activation function, Tanh function is applied to 1st and 2nd hidden layers and Sigmoid function is applied to the last layer.

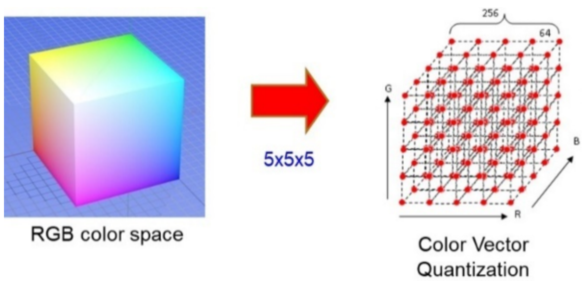


Figure 6. Color Feature Extraction Method with ALI [4]

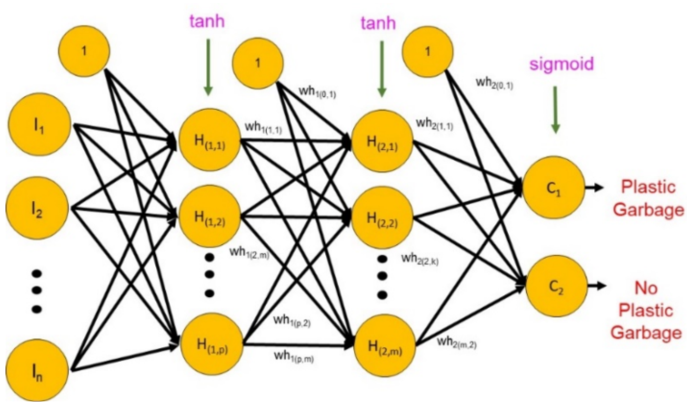


Figure 7. Model I of AI-Sensing: Multi perceptron Neural networks (with 2 Hidden Layers, 2 outputs) with ALI [4]

4.2. Evaluation Methods

In the evaluation experiments, we listed up three major evaluation methods: 1) Leave-one-out, 2) Cross Validation, and 3) Hold-out described in **Figure 8**. For a.) less than 100 data, we applied 1) Leave-one-out, and for b.) for the first trial and c.) 1,000 < data < 10,000, we applied 1) Leave-one-out and 3) Hold-out.

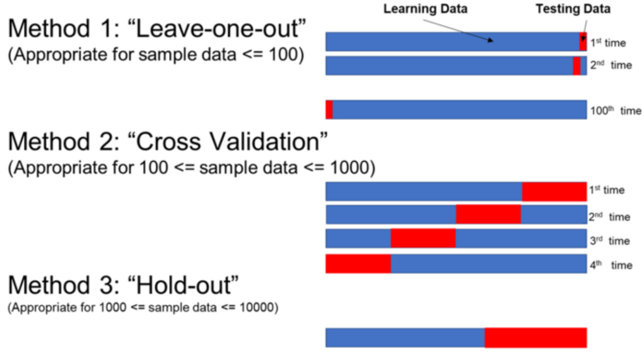


Figure 8. Typical Evaluation Methods for Machine Learning

4.2.1. Experiments with small datasets a.) less than 100 data

We set up the experimental environment and the learning and target images for Evaluation Test 1 with small data sets a.) less than 100 data as below:

Image Data for Leaning and Testing

1. 50 images for learning process: plastic garbage
2. 50 images for learning process: without plastic garbage
3. 100 images for testing: the same data of 1 and 2

The images are resized to 250-pixel height. We use 50 units of the 1st hidden layer and 30 units of the 2nd hidden layers, with learning rate (μ) = 0.05 and 5000 epochs.

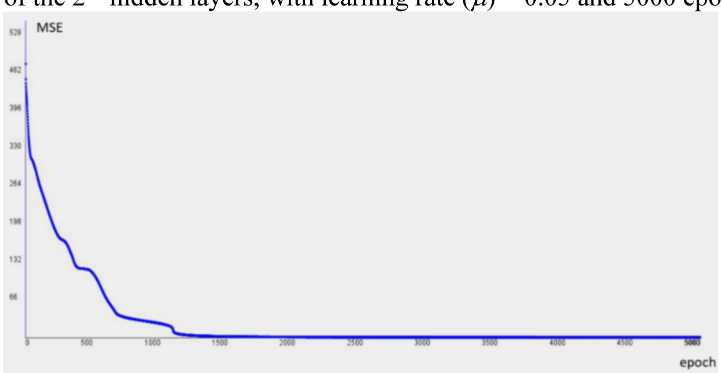


Figure 9. Calculation Results of Model I with a.) small data set (Evaluation Test 1): Mean Squared Error (MSE) using Gradient Descent (One of the Gradient Method Algorithms for Optimization problem)

We applied the evaluation method 1) Leave-one-out and calculated the error ratio and the accuracy rate. The testing results are shown in **Figure 9** and **Figure 10**. Mean Squared Error (MSE) is calculated using Gradient Descent (one of the Gradient Method Algorithms for optimization problem). The epoch (run time) was 5000 and the accuracy was 100% within 10 seconds. This result means that every target image is categorized to either "image with plastic garbage" or "image without plastic garbage" correctly.

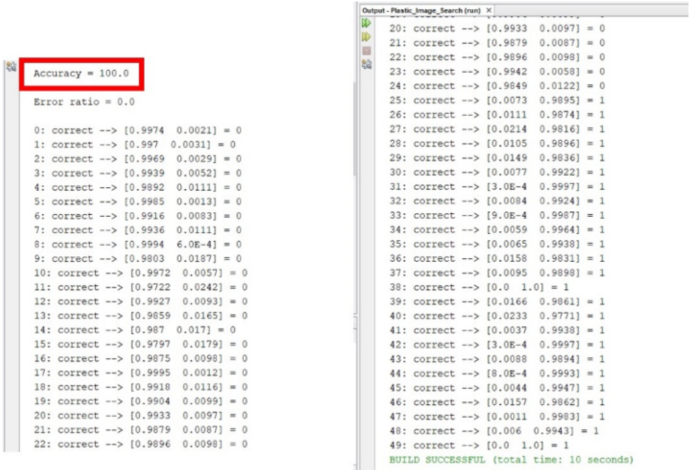


Figure 10. Calculation Results of Evaluation Test 1: Mean Squared Error (MSE) using Gradient Descent (One of the Gradient Method Algorithms for Optimization problem)

4.2.2. Experiments with relatively big datasets b.) 100 < data < 1,000 and c.) 1,000 < data < 10,000

We set up the experimental environment and the learning and target images for Evaluation Test 2 with a relatively large data sets b.) 100 < data < 1,000 and c.) 1,000 < data < 10,000 as below:

Collected Plastic Garbage Images

- 1st collection: garbage (48 images), without garbage (56 images)
- 2nd collection: garbage (654 images), without garbage (517 images)
- 3rd collection: garbage (160 images), without garbage (167 images)
- Total: garbage (862 images), without garbage (740 images)

The images are resized to 250 pixel height.

Dataset for testing

Garbage: 861 images (img no. 0-860)
  Learning: 500 images (img no. 0-499) - (virtually id 0-499 for training)
  Testing: 361 images (img no. 500-860) - (virtually id 0-360 for testing)
Not-Garbage: 739 images (img no. 861-1599)
  Learning: 500 images (img no. 861-1360) - (virtually id 500-999 for training)
  Testing: 239 images (img no. 1361-1599) - (virtually id 361-599 for testing)

Due to the higher variety of the colors in the image dataset, we use 80 units of the 1st hidden layer and 50 units of the 2nd hidden layers to give better separation in the vector space between the classes, with learning rate (μ) = 0.05 and 5000 epochs. We applied the evaluation method 1) Leave-one-out and 3) Hold-Out and calculated the error ratio and the accuracy rate. The test results are shown in **Figure 11** and **Figure 12**. Mean Square Error (MSE) is calculated using Gradient Descent (one of the Gradient Method Algorithms for optimization problem). The error ratio for 1) Leave-one-out was 0.7%, which means the accuracy rate was 99.3%. The error ratio for 3) Hold-Out was 22.17%, which means the accuracy rate was 78.83%. These results mean that every target image is categorized to either "image with plastic garbage" or "image without plastic garbage" correctly.

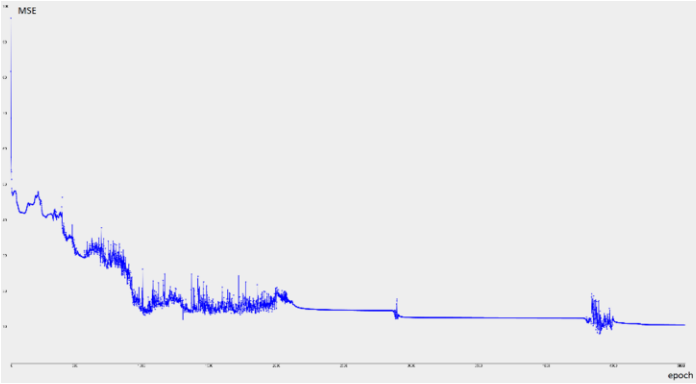
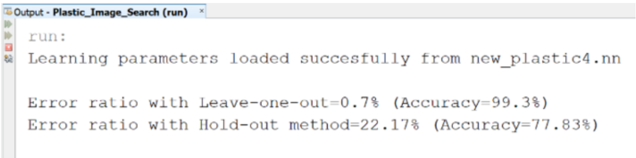


Figure 11. Calculation Results of Model I and b.) dataset (Evaluation Test 2): Mean Square Error (MSE) using Gradient Descent (One of the Gradient Method Algorithms for Optimization problem)



```
Output - Plastic_Image_Search (run)
run:
Learning parameters loaded succesfully from new_plastic4.nn

Error ratio with Leave-one-out=0.7% (Accuracy=99.3%)
Error ratio with Hold-out method=22.17% (Accuracy=77.83%)
```

Figure 12. Calculation Results of Mean Squared Error (MSE) using Gradient Descent (One of the Gradient Method Algorithms for Optimization problem)

4.3. Analysis on the results

By the evaluation method 1) Leave-One-Out, we acquired the good results **(99%-100%)** both with small data-set (100 training-data set) and relatively-big-data-set (1000 training-data set). By the evaluation method 3) Hold-Out, we acquired **appx. 80%** accuracy with relatively big data set (1000 training-data set). If we increase more learning data and perform “try-and-error” experiments with different parameter setting (eg. the learning rate (ἐ) and the momentum coefficient (μ), it is possible to get more accuracy. Also, by checking the error-cases (images) to make a ***regulation*** for training data collection, we are able to identify the cause of errors and the way to cope with.

5. AI-Sensing (Model II) and the substantiative experiments with actual local data

To examine the feasibility and effectiveness with real local data, a model for substantiative experiments (Model II) was created and a series of monitoring tests was conducted in this experiment. The detailed monitoring regulation and evaluation process with AI-Sensing are indicated and provided as “Manual for Capturing Photos” and “Manual for Uploading Photos” at UN-ESCAP CTL project [12]. By using these manuals, the actual monitoring experiments were conducted at Kalimas River and TMD River in Surabaya, Indonesia from Sep. 2020 to Sep. 2021 by a research partner group in Politeknik Electronika Negeri Surabaya (PENS), Surabaya, Indonesia. In addition, to check the applicability of the model, other substantiative experiments were conducted at

Ta Pi river and the watershed in Nakohn Si Tammarat, Tailand from May, 2021 to November, 2021 by a research partner group in Japan Space System (JSS), Japan.

5.1. Case I: Plastic Garbage on the city-river, Surabaya, Indonesia

Several fieldworks, experiments and evaluation of AI-Sensing were conducted with the local target images taken at TMD river in Surabaya. First, Kalimas river running through the city from the South to the North was a candidate for the analysis as an initial plan suggested by ESCAP. After the fieldwork and photo taking, the research group noticed that plastic garbage was not found so much in this river because of the Surabaya City's campaign of cleaning-up from 5 years ago. Then, we changed the target river from Kalimas to TMD river running through the city from the West to the East (**Figure 13**). The sets of learning data are shown in **Figure 14**, **Figure 15,** and **Figure 16** and the experimental results are shown in **Figure 17** and **Figure 18**.

Figure 13. Target rivers for monitoring (Kalimas river and TMD river) in Surabaya, Indonesia

We made experiment with use real images from the river of TMD in Surabaya city. In this experiment, we set these images consisting of 3 categories: (1) clean river (with 8 images, as shown in **Figure 14**), (2) the river containing non-plastic garbage (with 22 images, as shown in **Figure 15**), and (3) the river containing plastic garbage (with 36 images, as shown in **Figure 16**). Therefore, there are 3 output units of the Neural Network, which are clear, Non-Plastic Garbage and Plastic Garbage. For the input units, we set 125 inputs from 5x5x5 histogram bins of color scape. We still use 2 hidden layers consisting of 80 units in the 1st hidden layer and 50 units in the 2nd hidden layer. For the activation function, we use Tanh function for all hidden layers and Sigmoid for the output layer. For the learning process, we set 0.05 for the learning rate with 5000 epochs. The gradient descent from the learning process can be shown in **Figure 18**. These results show that our AI-Sensing performance is reasonably high.

Figure 14. Learning Data for "Clean" River in Surabaya, Indonesia for monitoring with AI-Sensing

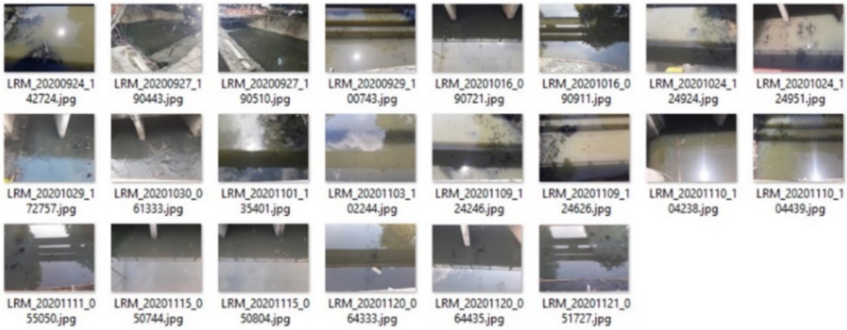


Figure 15. Learning Data for “Garbage” (non-plastic) in Surabaya, Indonesia for monitoring with AI-Sensing

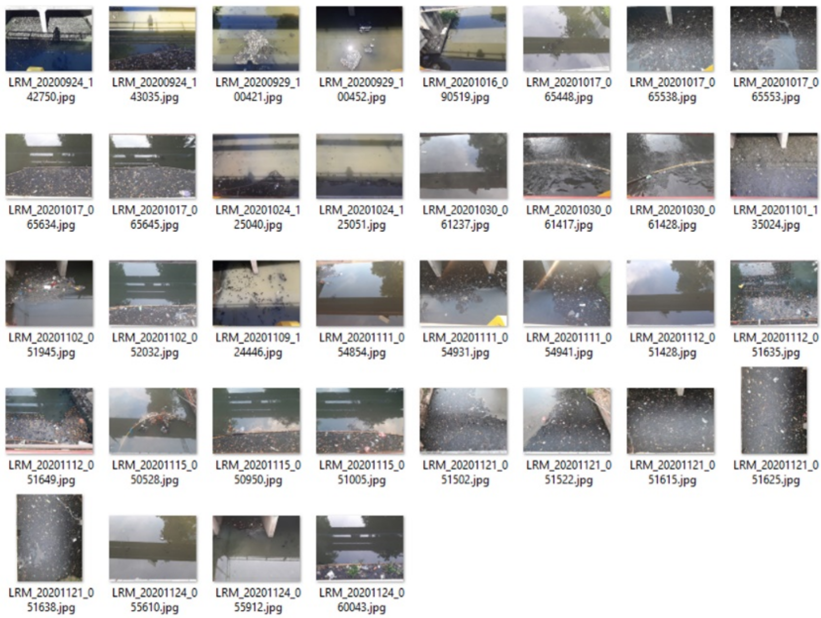


Figure 16. Learning Data for “Plastic Garbage” in Surabaya, Indonesia for monitoring with AI-Sensing

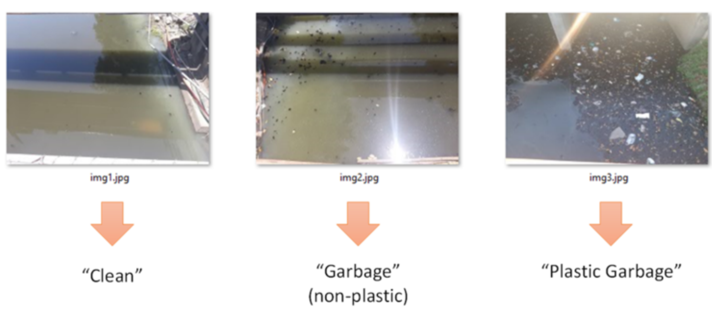


Figure 17. Example monitoring results of AI-Sensing for a case of Surabaya, Indonesia

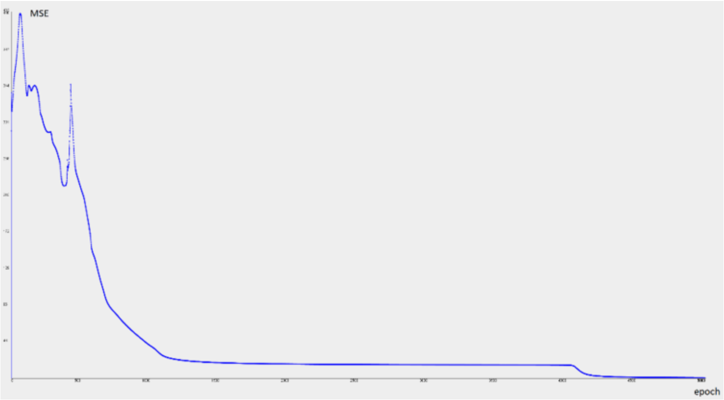


Figure 18. Evaluation (Precision) of AI-Sensing (Model 2) for a case of Surabaya, Indonesia

5.2. Case II: Plastic Garbage on the river with waterweed, Nakohn Si Thammarat, Thailand

In the Closing-the-Loop project lead by UN-ESCAP, 5D World Map System is expected to connect with other external systems such as GIS Data Sharing System (GDSS) developed by Japan Space Systems (JSS) [13] to collect and analyze actual local data as much as possible for the collaborative knowledge base creation and sharing. For the purpose, we have designed an integration method between 5D World Map System and other systems as shown in **Figure 5** at Section 3. Using the integrated two systems, we jointly conducted a series of substantiative experiments for the case of Nakhon Si Thammarat (NST), Thailand with the learning and test data sets collected by JSS. The fieldwork and data collection were conducted at Ta Pi river and the watershed in Nakohn Si Tammarat, Thailand during the period between September to November, 2021 (**Figure 19**).

Compared with Surabaya's case, the local image of plastic garbage in NST include a lot of green (aquatic plants) on the water. Thus, we jointly collected a set of images with green as a learning dataset (**Figure 20, Figure 21**), and created a specified model with NST's images to fit the local condition (**Figure 22**). The examples of experimental results are shown in **Figure 23**.

The accuracy of detection of plastic garbage was increased because of a specified model with NST's images to fit the local condition (green on the water or aquatic plants).

Figure 19. Target river and the watershed for monitoring, Nakohn Si Thammarat, Thailand

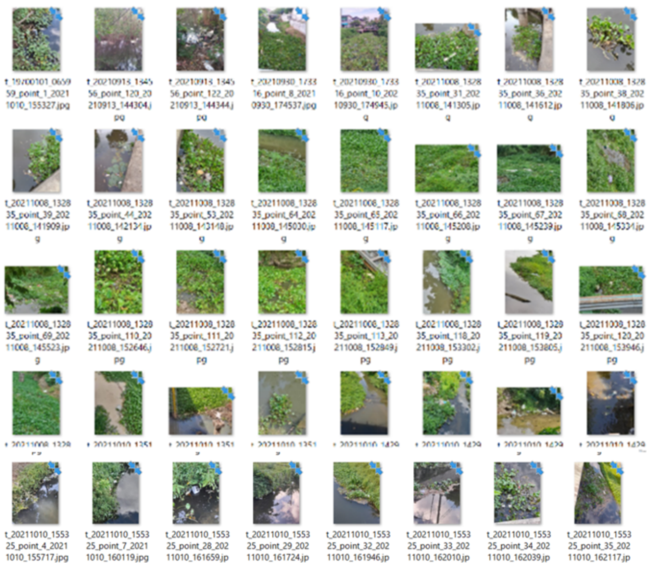


Figure 20. Learning Data of “Plastic Garbage” with green (aqua plants and bush) on the water

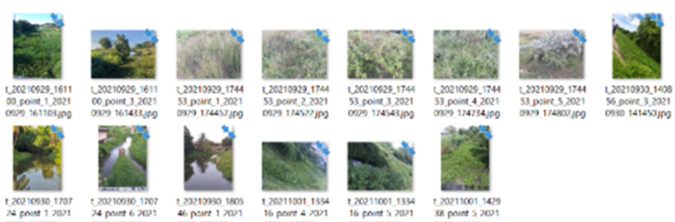


Figure 21. Learning Data of “Clean” with green (aqua plants and bush) on the water

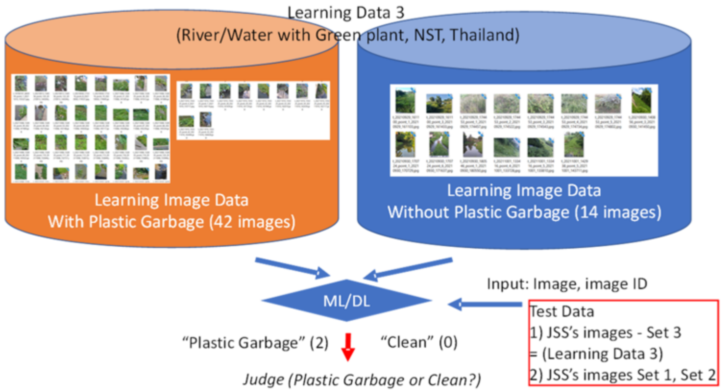


Figure 22. The evaluation and experimental datasets for the case of Nakhn Si Thammarat, Thailand with the learning and test data sets

Experiment 3 (Model I, Learning Data 3) with JSS's images –Set 3

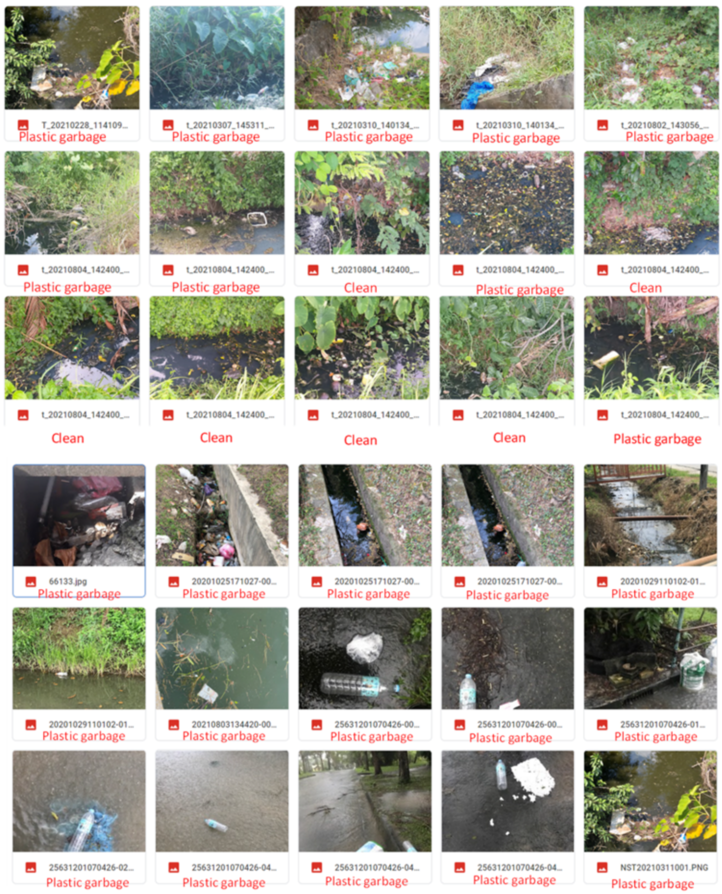


Figure 23. Evaluation and experimental results for the case of Nakhn Si Thammarat, Thailand with the localized learning and test data sets (Model 1, Learning Data 3)

5.3. Risk Categorization of Plastic Garbage

After identification of the plastic garbage inside the river, we also present an approach to categorize the plastic garbage into 4 categories, which are very low risk (the river tends to clear), low risk, middle risk, and high risk. This approach consists of 3 computational steps: (1) Color Filtering, (2) Neighborhood Windowing, and (3) Risk Determination. For the color filtering, we filter the color of an image by 64 closer color to white inside the RGB color space, as shown in Figure 25(a). Figure 25(b) shows the result of color filtering.

(a) (b)

Figure 24. Color filtering: (a) closer the white inside the RGB color space, and (b) result of color filtering

The next step is Neighborhood Windowing, which intends to reduce the sun light reflection from the filtered image after Color Filtering (**Figure 24**). The typical visual of sun light reflection, boundary of white neighborhoods is commonly wide. It needs to see the number of neighbors inside the window (size of the neighborhood). Here, we use the window 5x5, as shown in **Figure 25**. If number of white neighbors inside the window has adequacy, pixel x remains white. Otherwise, it will be converted into black. **Figure 26** shows the results of sun light reduction by using neighborhood windowing.

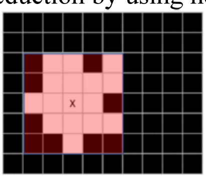


Figure 25. Neighborhood windowing with 5x5 windows

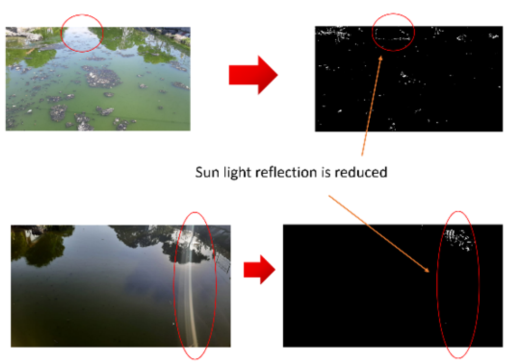


Figure 26. Results of sun light reduction by using neighborhood windowing

The next step is determination for the risk of the plastic garbage. First, we calculate the ratio of white color inside the image. Then, after making a series of empirical experiments, we set the threshold of the risk determination into 4 categories:

(1) White ratio < 0.003, the risk is very low (means that the river is clear from garbage)

(2) 0.003 ≤ Ratio < 0.005, the risk is low

(3) 0.005 ≤ Ratio < 0.01, the risk is middle

(4) Ratio ≥ 0.01, the risk is high

Figure 27 shows the effectiveness of our proposed approach of risk categorization.

Figure 27. Results of our approach for risk categorization

6. Output of 5D World Map System and the scenario for plastic reduction actuation

The examples of automatic mapping outputs of 5D World Map System with AI-Sensing module with collected plastic-garbage images actually in Surabaya (Indonesia), Bangkok (Thailand) and Kuala Lumpur (Malaysia) are shown in **Figure 28**, **29** and **Figure 30**.

The following scenario for use cases has been designed and proposed for a local situation analysis in the target four cities in the Closing the Loop project [12].

Step 1. A local user takes photos of river by smartphone or action cameras. In this step, it is recommended for users to follow the photo capturing regulation indicated in "Manual for Capturing Photos" [12] to increase the accuracy of detection of plastic garbage by AI-Sensing and adequately acquire geolocation and timestamp.

Step 2. Upload photos of the river onto the specific URL of Google Drive via GDSS by JSS [13] or onto 5D World Map System directly by following "Manual for Uploading Photos" [12].

Step 3. SPA-based 5D World Map System with AI-Sensing judges whether each photo includes plastic garbage or not by AI-Sensing function and returns the results to GDSS by a function call.

Step 4. 5D World Map System extracts the geolocation and time stamp information from the uploaded images from Exif, and automatically maps the images on the timeseries maps on 5D World Map System Web interface.

Step 5. The local user selects "plastic garbage", "non plastic garbage" or "clean river" from the category list of 5D World Map System to find out where is the place with plastic garbage, non-plastic garbage or clean river.

Step 6. The local user zooms in to the specific areas by map interface of 5D World Map System to focus on the details.

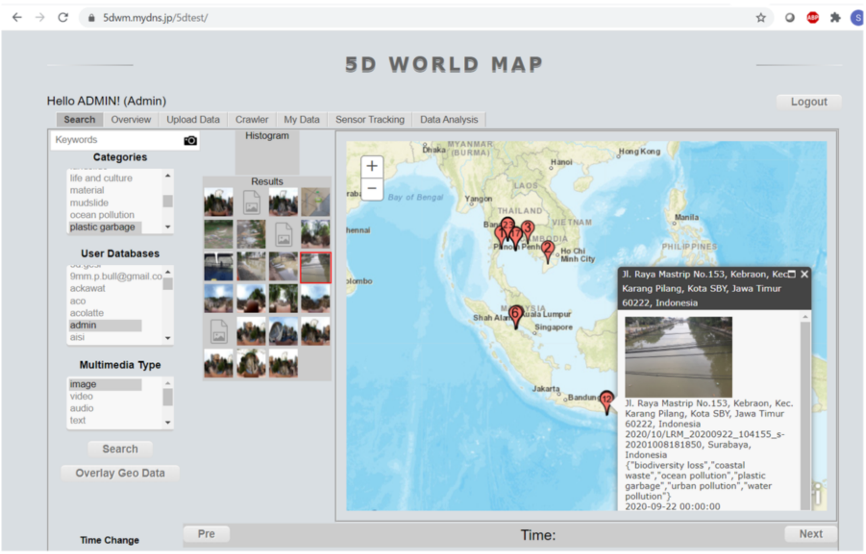
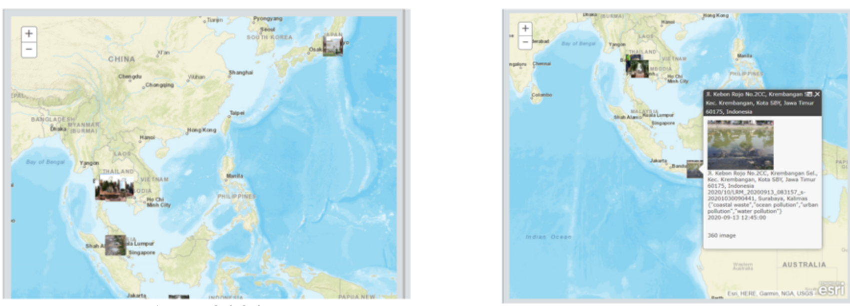
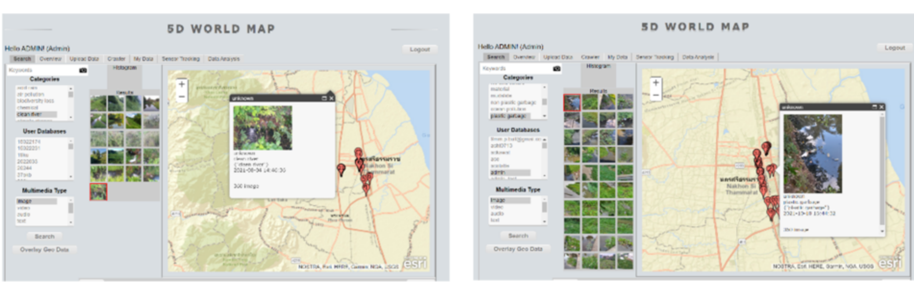


Figure 28. Actual Output of 5D World Map System with Image Search and AI-Sensing module with Collected Plastic-Garbage Images in Surabaya (Indonesia), Bangkok (Thailand) and Kuala Lumpur (Malaysia)



Aug. 2020 Sep. 2020

Figure 29. Actual Output of 5D World Map System with Time-series Analysis and AI-Sensing module with Collected Plastic-Garbage Images in Surabaya (Indonesia), Bangkok (Thailand) and Kuala Lumpur (Malaysia)



(a) (b)

Figure 30. Automatic-mapping results of AI-Sensing onto AI & 5D World Map System for the case of (a) “clean river” and (b) “plastic garbage” in Nakhn Si Thammarat, Thailand

7. Conclusion and Future Direction

In this paper, we have presented an important application of 5D World Map System, adding "AI-Sensing" functions for "Global Environment-Analysis" to make appropriate and urgent solutions to global and local environmental phenomena in terms of short and long-term changes. In this paper, focusing on the ocean plastic garbage issue, the methodology of AI-Sensing, the preliminary models and experiments on the accuracy of AI-Sensing, and the substantiative experiments on the feasibility and effectiveness of AI-Sensing with real local data are described. In addition, the example outputs of the integration of AI-Sensing algorithm and SPA-based 5D World Map System and an evaluation scenario for actual local users in target four cities in Closing the Loop project are introduced.

As a future direction of a collaborative project for ocean plastic-garbage reduction, we have expanded our research activities of SPA-based 5D World Map System with AI-Sensing functions to actual plastic garbage reduction projects and constructed a new partnership with Asia AI Institute (AAII) [14] in Musashino University, Japan and Thammasat University, Thailand. We have co-designed a function setting of "Plastic Garbage Detection and Reduction" with advanced technologies in the field of AI, Big-Data Analysis, Machine Learning, VR/AR, IoT and Robotics.

Acknowledgement

We would like to appreciate the members of ICT & Disaster Risk Reduction Division (IDD), UN ESCAP and Asia AI Institute (AAII), Musashino University and Thammasat University for their significant discussions and experimental studies.

References

[1] Kiyoki Y, Chen X. Contextual and Differential Computing for the Multi-Dimensional World Map with Context-Specific Spatial-Temporal and Semantic Axes. In: Information Modelling and Knowledge Bases XXV; Vol.260; IOS Press; 2014; p. 82-97.

[2] Kiyoki Y, Sasaki S, Nguyen NT, Nguyen TND. Cross-cultural Multimedia Computing with Impression-based Semantic Spaces, In: Conceptual Modelling and Its Theoretical Foundations, Lecture Notes in Computer Science; 2012; Springer; p.316-328.

[3] Kiyoki Y, Chen X. A Semantic Associative Computation Method for Automatic Decorative-Multimedia Creation with "Kansei" Information. (Invited Paper), Proceedings of the Sixth Asia-Pacific Conferences on Conceptual Modelling (APCCM 2009); Conferences in Research and Practice in Information Technology Series; Vol. 96; 2009 January 20-23; ISSN 1445-1336.

[4] Barakbah AR, Kiyoki Y. An Image Search System with Analytical Functions for 3D Color Vector Quantization and Cluster-based Shape and Structure Features. In: Information Modelling and Knowledge Bases XXI; Vol. 206; IOS Press; 2010; p. 169-187.

[5] Sasaki S, Takahashi Y, Kiyoki Y. The 4D World Map System with Semantic and Spatiotemporal Analyzers. In: Information Modelling and Knowledge Bases Vol.XXI; Vol. 206;IOS Press; 2010, p. 1-18.

[6] Sasaki S, Kiyoki Y. Real-time Sensing, Processing and Actuation Functions of 5D World Map System: A Collaborative Knowledge Sharing System for Environmental Analysis. In: Information Modelling and Knowledge Bases Vol. XXVII; Vol. 280; IOS Press; 2016; p. 220-239.

[7] Kiyoki Y, Chen X, Sasaki S, Koopipat C. A Globally-Integrated Environmental Analysis and Visualization System with Multi-Spectral & Semantic Computing in "Multi-Dimensional World Map". In: Information Modelling and Knowledge Bases XXVIII; Vol. 292; 2017; p.106-122.

[8] Sasaki S, Kiyoki Y. Analytical Visualization Functions of 5D World Map System for Multi-Dimensional Sensing Data. In: Information Modelling and Knowledge Bases XXIX; Vol. 301; IOS Press; 2018; p.71-89.

[9] Kiyoki Y, Chen X, Veesommai C, Wijitdechakul J, Sasaki S, Koopipat C, Chawakitchareon P. A Semantic-Associative Computing System with Multi-Dimensional World Map for Ocean-Environment Analysis. In: Information Modelling and Knowledge Bases XXX; Vol.312; IOS Press; 2019; p. 147-168.
[10] Kiyoki Y, Chen X, Veesommai C, Rachmawan IEW, Chawakitchareon P. A SPA-based Semantic Computing System for Global & Environmental Analysis and Visualization with "5-Dimensional World-Map": Towards Environmental Artificial Intelligence. In: Information Modelling and Knowledge Bases XXXI; Vol. 321; IOS Press; 2020; p. 285-305.
[11] Sasaki S, Kiyoki Y, Sarkar-Swaisgood M, Wijitdechakul J, Rachmawan IEW, Srivastava S, Shaw R, Veesommai C. 5D World Map System for Disaster-Resilience Monitoring from Global to Local: Environmental AI System for Piloting SDG 9 and 11. In: Information Modelling and Knowledge Bases XXXI; Vol. 321; IOS Press; 2020; p. 306-323.
[12] Closing-the-Loop, UN-ESCAP. https://www.unescap.org/projects/ctl (accessed September 10, 2022)
[13] GIS Data Sharing System (GDSS) by Japan Space Systems (JSS). https://www.jspacesystems.or.jp/en/project/inter/topics/1176.html (accessed September 10, 2022)
[14] Asia AI Institute (AAII): https://ds.musashino-u.ac.jp/aaii/
[15] Sesulihatien WT, Sasaki S, Kiyoki Y, Harsono T, Basuki A, Safie A, Local-Regional-Global Analysis on Infectious Disease with Analytical Visualization Functions of 5D World Map System: A Case of Comparative Analysis on Dengue Fever Spreading in Indonesia and Malaysia. In: Malaysian Journal of Tropical Geography, June 2016.
[16] Kiyoki Y, Chawakitchareon P, Rungsupa S, Chen X, Samlansin K. A Global & Environmental Coral Analysis System with SPA-Based Semantic Computing for Integrating and Visualizing Ocean-Phenomena with "5-Dimensional World-Map". In: Information Modelling and Knowledge Bases XXXII; IOS Press; 2020; p. 76-91.
[17] Rachmawan IEW, Kiyoki Y. A New Approach of Semantic Computing with Interval Matrix Decomposition for Interpreting Deforestation Phenomenon. In: Information Modelling and Knowledge Bases XXX; Vol.312; IOS Press; 2019; p.353-368.
[18] Chen X, Kiyoki Y. A Semantic Orthogonal Mapping Method through Deep-learning for Semantic Computing. In: Information Modelling and Knowledge Bases XXX; Vol.312, IOS Press; 2019: p.39 -60.
[19] Wijitdechakul J, Kiyoki Y, Koopipat C. An environmental-semantic computing system of multispectral imagery for coral health monitoring and analysis. In: Information Modelling and Knowledge Bases XXX; Vol.312; IOS Press; 2019; p.293-311.
[20] Rachmawan IEW, Kiyoki Y. Semantic Multi-Valued Logic for Deforestation Phenomena Interpretation. In: Information Modelling and Knowledge Bases XXXI; Vol. 321; IOS Press; 2020; p. 401-418.
[21] Chawakitchareon P, Thalheim B, Kiyoki Y. Water Quality Index Analysis and Prediction: A case study of canals in Bangkok Thailand. In: Information Modelling and Knowledge Bases XXXI; Vol. 321; IOS Press; 2020; p. 419-429.
[22] Chen X, Kiyoki Y. On Logic Calculation with Semantic Space and Machine Learning. In: Information Modelling and Knowledge Bases XXXI; Vol. 321; IOS Press; 2020; p. 324-343.
[23] Kiyoki Y, Thalheim B, Duží M, Jaakkola H, Chawakitchareon P, Heimbürger A. Towards a Great Design of Conceptual Modelling. In: Information Modelling and Knowledge Bases XXXI; Vol. 321; IOS Press; 2020; p. 531-544.
[24] Veesommai C, Kiyoki Y, Sasaki S. A Multi-Dimensional River-Water Quality Analysis System for Interpreting Environmental Situations. In: Information Modelling and Knowledge Bases XXVIII; Vol. 292; IOS Press; 2017; p.43-62.
[25] Rachmawan IEW, Kiyoki Y. Semantic Spatial Weighted Regression for Realizing Spatial Correlation of Deforestation Effect on Soil Degradation. Proceedings of the International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC2017); Sep. 2017; Surabaya, Indonesia. Doi: 10.1109/KCIC.2017.8228566
[26] Wijitdechakul J, Kiyoki Y, Sasaki S, Koopipat C. UAV-based Multispectral Aerial Image Retrieval using Spectral Feature and Semantic Computing. Proceedings of the International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC2017); Sep. 2017; Surabaya, Indonesia. Doi: 10.1109/KCIC.2017.8228571