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The Detection of Plastic Waste Using UAV-based Multispectral Data and Deep Learning

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Abstract.
Background/Objectives: With the increase of leisure and recreational activities, green spaces are being used more frequently, which is producing more plastic waste. Against the backdrop, it is necessary to protect and preserve the ecosystem by detecting plastic waste using multispectral data and deep learning technology.
Methods/Statistical analysis: In order to detect plastic waste dumped into green spaces, this study performed a deep learning and analysis of the spectral characteristics of plastic waste, which are different from the vitality of plants in green spaces, using artificial intelligence technology and data acquired through multispectral sensors on UAVs.
Findings: A deep learning model was learned and processed with different band combinations of multispectral video to detect plastic waste in green or living spaces. The prediction accuracy was the highest with AdaBoost followed by Random Forest. As for image combinations, combining RGB, Rededge, NIR, and others had the highest accuracy. Therefore, AdaBoost and RGB, Rededge, and NIR image combinations seem to provide the best applicability.
Improvements/Applications: These research results are expected to be used as basic information to apply deep learning to various classification techniques related to land cover classification and to contribute to preventing environmental pollution and minimizing ecosystem disturbance through plastic waste management.

Keywords: UAV, Deep Learning, Plastic Waste, Multispectral, AdaBoost, Random Forest

1. INTRODUCTION

Urban managers want to monitor the state and change of artificial structures, topography, and vegetation to manage the spatial structure and environment of urban areas [1]. In recent years, various environmental changes, such as climate change, have caused significant alteration and damage to the land cover. In addition, the frequency and amount of plastic waste disposal are increasing due to the increased use of green spaces for leisure and recreational activities. Accordingly, it is necessary to develop and apply land cover classification technology as a foundation to protect and manage the natural environment based on scientific collection and analysis of information [2-4]. Typical land cover classification methods for plastic waste detection include classification through on-site investigation, measurement, and supervision, and supervised image classification using multispectral images through aerial surveys and satellite sensors [5]. Land cover classification methods such as field surveys and measurements are limited in terms of spatial and temporal classification. While land cover classification by space and aerial platforms can secure a certain level of reliability in both quantitative and qualitative aspects in wide areas, it is expensive and cannot be provided in a timely manner. The recent UAV-based land cover classification and plastic waste detection technologies, however, have outstanding strengths in terms of quantity, quality, and cost, which are expected to establish the foundation of knowledge necessary for waste detection. In addition, the multispectral sensor can provide information on spectral characteristics required for the detection of land and marine waste, and the multispectral sensor mounted on a UAV can acquire waste distribution data with high spectrum and geospatial resolution; it can be used as an effective platform to detect and quantify waste [6-11]. However, there are many limitations in the accuracy of plastic waste detection by the existing land cover classification methods. Therefore, it is necessary to apply artificial intelligence technology to improve this accuracy. Artificial intelligence technologies, such as deep and machine learning, are widely used, but deep learning is the most popular in detecting changes in land cover. In this regard, this study aims to perform high-accuracy plastic waste detection using technology with human judgment where the multispectral data acquired through the UAV platform is applied to machine learning. The outcome will be provided as basic information for the detection and monitoring of plastic in green spaces and aquatic environments.

2. OBJECT CLASSIFICATION USING MULTISPECTRAL DATA AND ARTIFICIAL INTELLIGENCE

Electromagnetic waves in the NIR region are the most used raw data for plastic waste detection. In general, the NIR region exists between the end of the red region (wavelength 700 nm) and the mid-infrared region (wavelength 2500 nm). As shown in Fig. 1 [12], plastic materials have their own absorption band region for electromagnetic waves. Therefore, it is possible to analyze waste quantitatively and qualitatively by using the materials' unique absorption characteristics in the NIR spectrum region.

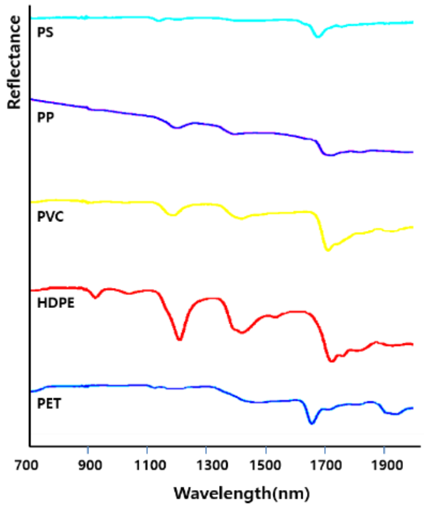

Figure 1. Characteristics of Reflectance Spectrum of Plastic

Table 1: Classification of Artificial Intelligence Technologies

Items	Contents		
Supervised Learning	Classification	Regression	
Unsupervised Learning	Clustering	Transform	Association
Reinforcement Learning	-		

The multispectral sensor mounted on the UAV platform can detect waste by collecting multispectral data, including the NIR area. Due to various environmental factors, however, it may not be possible to obtain the desired quality or quantitative results. In this case, the accuracy of the results can be effectively improved by applying the learning and prediction technology of artificial intelligence. Artificial intelligence extracts and learns the features of data through computers to find out the rules for a certain phenomenon. Such learning is called machine learning, and it is a technology that delegates human judgment to the machine. Machine learning can be classified into specific technologies according to three learning methods as shown in Table 1.

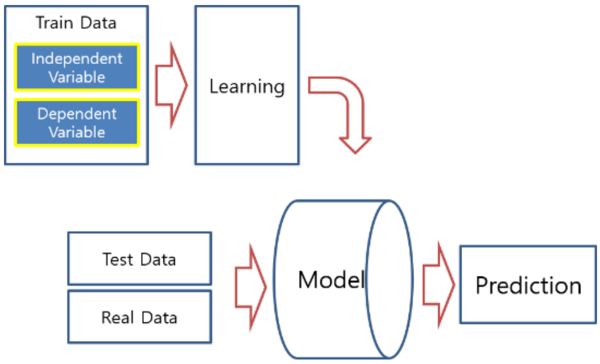

Figure 2. Process of Artificial Intelligence Analysis

Artificial intelligence performs data, learning, and predictions according to the analysis procedure shown in Fig. 2. Supervised learning includes classifications and sessions and requires past data. The past data should be divided into causes and results. The causes correspond to independent variables, including temperature, and the results are dependent variables, including sales volume according to temperature, which is a rowset connected with the independent variables through a causal relationship. When this type of causal relationship is known and trained in a learning algorithm, the relationship is identified and a model is created. When new, independent variables are entered into the model, dependent variables calculated by the model are provided. At this time, it must be checked if the data type of the dependent variables is numeric or text. If it is numeric, it is quantitative data; if it is text, it is called a categorical type. Categorical types are characterized by finite candidates for variables. That is, dependent variables must belong to quantitative or categorical data. In this case, the quantitative data format uses regression, while the categorical data uses classification. The difference in learning flow and feature extraction distinguishes machine learning from deep learning. Machine learning evaluates and predicts new data by manually extracting and directly learning the data features. While classified as a part of machine learning, deep learning automatically extracts data features and learns them using the structure of an artificial neural network. In general, the types of machine learning or deep learning can be classified into object classification, object detection, and segmentation. Object classification refers to predicting a single label for input data, while object detection predicts the label of input data and detects the location information of the object and displays it as a bounding box. Object segmentation predicts the label of the entire input data and predicts the object area at the same time.

Table 2 shows the main models and techniques of artificial intelligence. The process of acquiring data and utilizing artificial intelligence technology on the UAV platform is as follows:

Table 2: Major Models and Characteristics of Artificial Intelligence

Algorithms	Data Format	Type	Predict Accuracy	Learning Speed	Predict Speed
SVM	Number, Category	Regression, Classification	Low	Fast	Slow
KNM	Number, Category	Regression, Classification	Low	Fast	Slow
Linear Regression	Number	Regression	Low	Fast	Fast
Logistic Regression	Category	Classification	Low	Fast	Fast
Naïve Bayes	Category	Classification	Low	Fast	Fast
Decision Trees	Number, Category	Regression, Classification	Low	Fast	Fast
Random Forest	Number, Category	Regression, Classification	High	Slow	Moderate
AdaBoost	Number, Category	Regression, Classification	High	Slow	Fast
Neural Network	Number, Category	Regression, Classification	High	Slow	Fast

3. DATA CONSTRUCTION AND ANALYSIS

3.1. RESEARCH PROCEDURE

As shown in Fig. 3, this study acquired the coordinates of GCP through a GNSS static survey in order to perform UAV photogrammetry by applying the GCP-based georeferencing method. Multispectral video was captured through GNSS-based UAV aerial surveying technology, and the camera position was adjusted through post-processing. The result was geo-tagged with the center coordinates of the image. After that, spatial image information, such as point clouds and orthophotograph, was produced through aerial triangulation. The multispectral orthophotograph was produced with RGB and NDVI images, and learning and evaluation data was constructed by selecting a plastic waste object, a target to detect. In order to classify plastic waste by applying artificial intelligence techniques with multispectral data, it is necessary to construct learning and evaluation data.

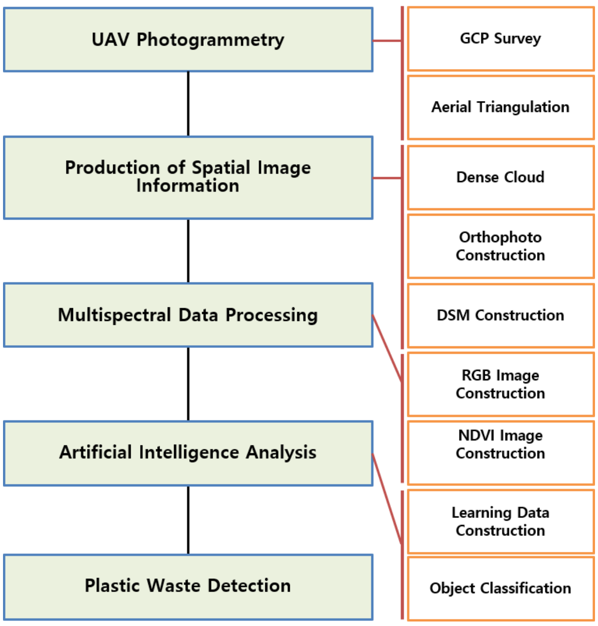

Figure 3. Research Procedure

3.2. DATA CONSTRUCTION AND PROCESSING

The study sites are indicated in Fig. 4. Coordinate results for the five points of GCP were obtained through a GNSS static survey, and multispectral video was acquired using DJI's Matrice600Pro and Micasense's ALTUM sensor. The resolution of the sensor was 2064 × 1544 (3.2 MP per EO band), the flight level 120 m, the GSD (Ground Sample Distance) 5.2 cm, and the end and side laps 80% and 70%, respectively. DSM and orthophoto were produced through georeferencing using GCP and aerotriangulation.

Figure 4. Orthophotograph of Research Areas

Multispectral video was analyzed using artificial intelligence models, including AdaBoost, CN2 rule induction, Random Forest, Tree, Neural Network, Naive Bayes, SVM, SGD (Stochastic Gradient Descent), KNN, and Logistic Regression models, using "Orange." The workflow for the input, pre-processing, visualization, clustering, classification, etc. of the analysis data is shown in Fig. 5.

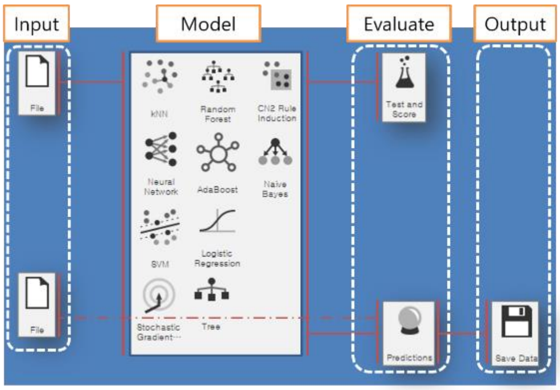

Figure 5. Workflow of Artificial Intelligence Analysis

3.3. ANALYSIS AND EVALUATION BY MODEL

This study tried to select the optimal band region by clustering the multispectral data to be input into the artificial intelligence models into six band regions: RGB, RGB + Rededge, NIR, NIR + Rededge, RGB + Rededge + NIR, and NDVI. Five data points were put into the artificial intelligence models for learning and evaluation (cross-validation accuracy estimation), and the evaluation result, AUC (Area Under an ROC Curve), is shown in Table 3.

AUC refers to the area under the ROC (Receiver Operation Characteristic) curve as an index for evaluating the accuracy of the test. It shows how many cases were accurately predicted out of all the data. The closer to 1 the AUC score is, the better the classification performance of the model. However, the recall should also be considered together with the AUC as shown in Table 4. Recall is the ratio that the model predicted as true. As reference statistics, the F1 score is a scale used for the proper mix of precision and recall and consists of a weighted harmonic average of precision and recall. The larger the value, the better it can be predicted. Precision refers to the accuracy rate of positively predicted values. In this study, only the AUC and Recall were reviewed.

The random sampling technique was used for test and score calculation, where the repeat train/test of 5 and the training set size of 70% were applied. After evaluation, "RGB + Rededge + NIR" was selected for plastic waste detection by reviewing the AUC. As for artificial intelligence, Random Forest and AdaBoost were chosen by considering both AUC and Recall. For the evaluation of the predicted results, as shown in Table 5, six objects (Fig. 6) were selected in the target area, and the prediction accuracy of the models was evaluated by comparing the detected results and areas.

Table 3: Evaluation Results (AUC)

Model	RGB	RGB+Rededge	NIR	NIR+Rededge	RGB+Rededge+NIR	NDVI
KNN	0.928	0.924	0.829	0.951	0.963	0.898
Tree	0.856	0.858	0.754	0.791	0.861	0.854
SVM	0.781	0.812	0.765	0.888	0.873	0.887

SGD	0.628	0.675	0.605	0.688	0.765	0.584
Random Forest	0.955	0.961	0.853	0.916	0.976	0.912
Neural Network	0.915	0.932	0.791	0.920	0.970	0.873
Naive Bayes	0.915	0.920	0.756	0.860	0.947	0.85
Logistic Regression	0.734	0.762	0.643	0.753	0.816	0.769
CN2 rule induction	0.706	0.801	0.524	0.532	0.805	0.774
AdaBoost	0.850	0.846	0.724	0.795	0.856	0.774

Table 4: Evaluation Results (Recall)

Model	**RGB**	**RGB+Rededge**	**NIR**	**NIR+Rededge**	**RGB+Rededge+NIR**	**NDVI**
KNN	0.792	0.755	0.698	0.736	0.849	0.925
Tree	0.642	0.623	0.453	0.604	0.811	0.906
SVM	0.434	0.491	0.472	0.585	0.623	0.755
SGD	0.472	0.472	0.321	0.585	0.585	0.698
Random Forest	0.962	0.943	0.811	0.925	0.943	1.000
Neural Network	1.000	1.000	1.000	1.000	1.000	1.000
Naive Bayes	0.585	0.660	0.434	0.642	0.755	0.811
Logistic Regression	0.264	0.264	0.264	0.264	0.302	0.453
CN2 rule induction	0.962	0.962	0.811	0.849	0.981	0.981
AdaBoost	1.000	1.000	1.000	1.000	1.000	1.000

Table 5: Evaluation of Detection Results

	Evaluation Criteria(Plastic(m^2))	**AdaBoost(m^2)**	**Plastic-AdaBoost(m^2)**	**Random Forest(m^2)**	**Plastic-Random Forest(m^2)**
Object 1	0.088	0.044	0.044	0.038	0.050
Object 2	0.118	0.083	0.035	0.091	0.027
Object 3	0.097	0.040	0.057	0.039	0.058
Object 4	0.066	0.042	0.024	0.055	0.011
Object 5	0.214	0.199	0.015	0.171	0.043
Object 6	0.290	0.263	0.027	0.249	0.041
Average		0.034		0.038	

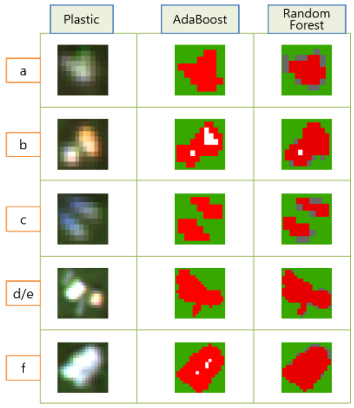

Figure 6. Evaluation Results by Model

As a result of evaluating the prediction accuracy of AdaBoost and Random Forest, which were selected as the learning models, and the “RGB + Rededge + NIR” band area that was selected by the AUC and Recall for plastic waste detection, the AdaBoost model showed higher accuracy than Random Forest as shown in Table 5. As a result of calculating the difference between the actual area of the evaluating object and the area calculated by the two models (AdaBoost and Random Forest), there was a difference of 0.034㎡ and 0.038㎡, respectively, and AdaBoost recorded 0.004㎡ less error than Random Forest. Fig. 7, 8, and 9 show the results of plastic waste detection for the research areas using the two models.

As a result of detecting plastic waste using AdaBoost and Random Forest, AdaBoost recorded 61,560㎡ and Random Forest 125,281㎡ as shown in Fig. 9. Such a difference between the two models was due to the similar characteristics of the reflectance spectrum of plastics and rocks. In particular, the AdaBoost model showed similar reflectance between plastic waste, curbstones, and rocks, while the Random Forest model showed similar reflectance between plastic waste, curbstones, rocks, and the color of asphalt concrete, indicating more effect on the classification results than AdaBoost. In general, AdaBoost showed better detection accuracy than Random Forest. It is considered that the number of individual samples for learning should be increased to improve the overall detection accuracy. The number of samples for plastic waste should be increased for AdaBoost, while the number of learning samples for plastic waste as well as that for each color of asphalt concrete should be increased for Random Forest.

Figure 7. Evaluation Results by Model(AdaBoost)

Figure 8. Evaluation Results by Model(Random Forest)

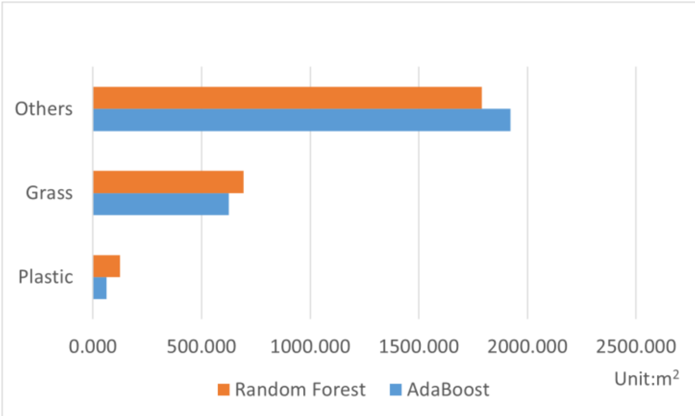

Figure 9. Statistics of Detection Results

4. CONCLUSION

The results of investigating plastic waste detection using multispectral sensors mounted on a UAV and deep learning and analysis are as follows:

In order to detect plastic waste, deep learning models were investigated and analyzed using different band combinations of multispectral video. As a result, the band area to be used for plastic waste detection was "RGB + Rededge + NIR." In addition, as a result of comparing and evaluating the artificial intelligence models to be applied to the study, the prediction error of the AdaBoost model was 0.004㎡ less than that of the Random Forest model, indicating that the former has a higher prediction accuracy than the latter.

As a result of detecting plastic waste using a deep learning model, there was a difference of 63.72㎡ in the results of AdaBoost and Random Forest. The cause of this difference between the two models was similarity in the reflectance spectrum of plastics and nearby rocks and asphalt concrete.

The research results are expected to be used as basic information to apply deep learning to plastic waste detection and various land cover classification techniques. In addition, they are expected to contribute to preventing environmental pollution and minimizing ecological disturbance by effectively supporting plastic waste management in different ways.

5. ACKNOWLEDGMENT

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