AI-Based Automatic Detection of Water Bodies in Surface Reflectance Images: Focusing on Korea's National Territorial Satellite ARD Data

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1. Introduction

The Analysis Ready Data (ARD) produced by Korea's National Territorial Satellite No. 1 (CAS500-1) includes surface reflectance images and auxiliary information. The auxiliary information consists of binary masks for water bodies, clouds, and valid areas. The water body mask is created by overlaying a meticulously geo-corrected national satellite with the Korean Peninsula Water Body Map, which is based on the national base map. This water body map is manually crafted and requires periodic updates, a process that demands considerable time and resources. Consequently, there is a significant need for automated water body detection technologies to increase efficiency and reduce costs. This study aims to develop a technology for automatically detecting water bodies using ARD images. It is anticipated that the automatic water body detection technology can be applied to satellite and hyperspectral imagery that incorporates surface reflectance. For this research, ARD data from CAS500-1 was utilized.

2. MATERIALS AND METHODS

Data Used: The study employed ARD that has been both radiometrically and atmospherically corrected. These images were segmented into 1:5000 tile with a Ground Sampling Distance (GSD) of 2 meters. Additionally, true mask used the water body mask of CAS500-1.

Data Preprocessing:

- Normalization: Applied min/max normalization to scale the pixel values between 0 and 1, which helps

- Resizing: Images were resized to 256x256 pixels, standardizing input data size for the neural network, which facilitates efficient training and reduces computational load.

Model Employed: The U-net model, a convolutional network designed for fast and precise segmentation tasks, was chosen for its efficiency in handling spatial hierarchies for image segmentation.

Data Split: The dataset was divided as follows: 70% for training, 15% for validation, and 15% for testing. This split ensures robust training while allowing for comprehensive validation and testing to evaluate the model's performance.

Training Methodology:

- Epochs: The model was trained for 20 epochs to allow sufficient learning without overfitting.
- Batch Size: A batch size of 4 was used, optimizing the balance between memory usage and model update frequency.

Prediction Methodology: The model predicts water bodies by classifying areas where the prediction probability is greater than 0.5 as true water bodies, ensuring accurate identification and segmentation.

3. Results and Discussion

The results from Figures 1 through 4 demonstrate that the experimental model effectively predicts water bodies. Specifically, Figures 1 and 3 illustrate precise detection of water bodies corresponding to the terrain and sea level variations. In Figure 1, the intertidal zone is accurately predicted based on the sea level at the time of image capture. Figure 3 also shows that the model successfully differentiates non-water areas based on the altered terrain. Additionally, as shown in Figure 4, boats marked with red circles are detected as non-water bodies. This indicates accurate object detection since the boats are present in the images but are not included in the True Mask. However, as seen in Figure 5, there are instances where water bodies are incorrectly detected. This is presumed to be due to the inadequate representation of the sea surface reflectance in the original imagery. Table 1 presents the scores for each metric used to evaluate the performance of the model.

Accuracy indicates how closely the model's predictions match the actual outcomes, while precision refers to the proportion of predicted water body areas that are true water bodies. The F1 score, a harmonic mean of accuracy and precision, reflects the balance between these two metrics. However, the Intersection over Union (IoU) score, which measures the ratio of the intersection to the union of predicted and actual values, was relatively low. This lower IoU score is attributed to the True Mask not accurately capturing the water bodies in updated original images that fail to reflect actual terrain changes or variations in sea level height.

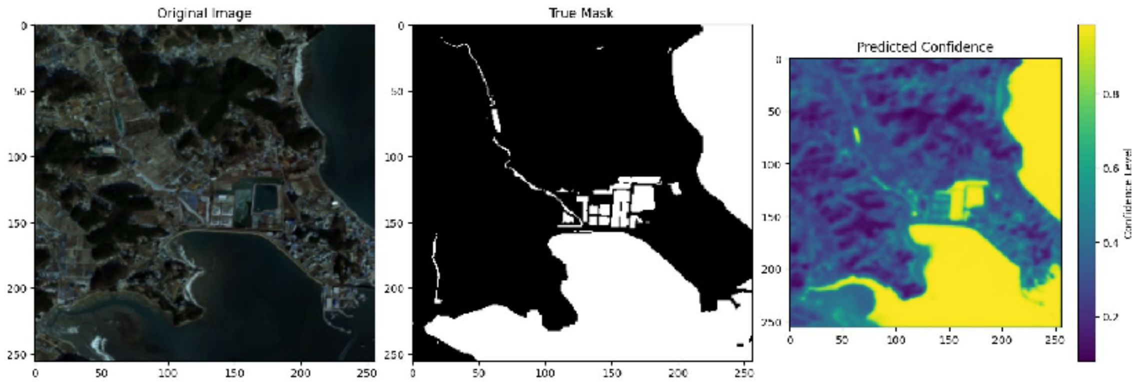

Figure 1: Comparison of Water Body Detection Data 1.

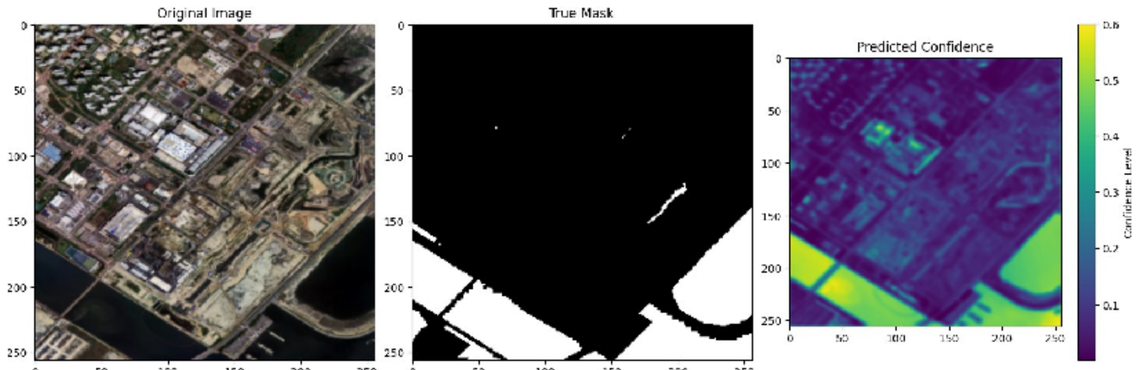

Figure 2: Comparison of Water Body Detection Data 2.

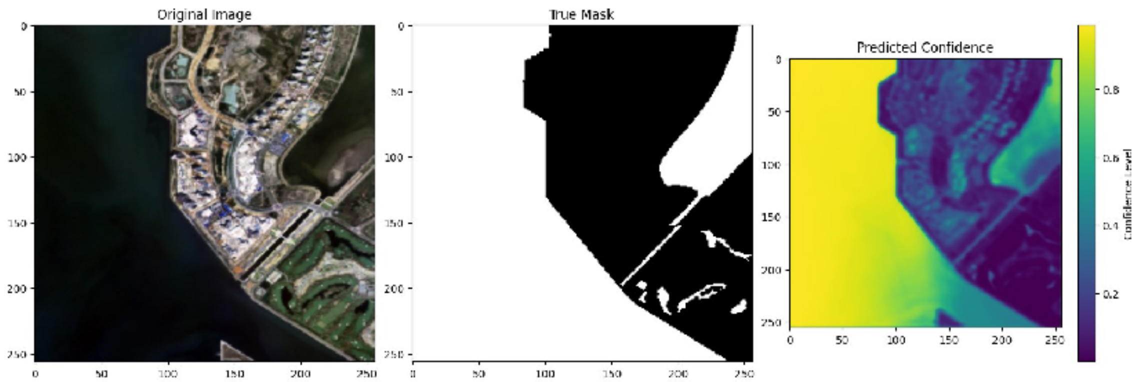

Figure 3: Comparison of Water Body Detection Data 3.

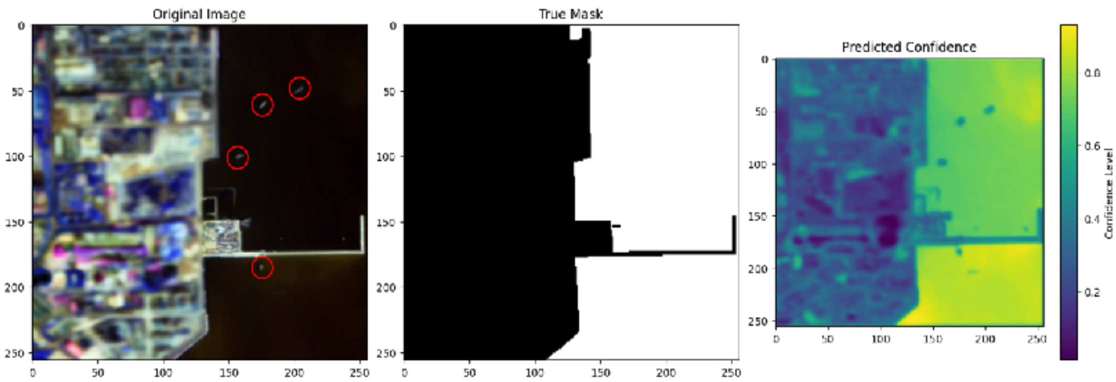

Figure 4: Comparison of Water Body Detection Data 4.

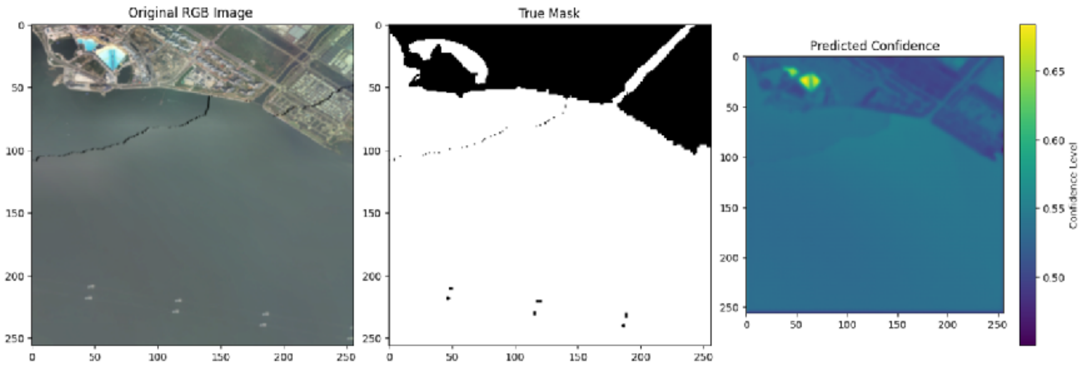

Figure 5: Comparison of Water Body Detection Data 5.

Evaluation Metrics	Accuracy	Precision	F1 Score	IoU Score
Score	0.8625	0.9836	0.8056	0.6743

Table 2: Results for Water Body Detection Model.

4. Conclusion

This study confirmed the feasibility of using artificial intelligence models to automatically detect water bodies by leveraging the spectral characteristics of water bodies in surface reflectance imagery. Overall, the detection of water bodies was successful. however, insufficient atmospheric correction in some data led to false detections. The surface reflectance imagery used in this study was generated using atmospheric information available online. Actual field data necessary for accurately reproducing the reflectance characteristics of coastal areas were not considered, which posed challenges in precisely replicating coastal reflectance.Future research will need to thoroughly consider these aspects to further enhance water body detection technologies. Building on the developments from this study, there are plans to develop object detection technologies using hyperspectral imagery from unmanned aerial vehicles.

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