Improving GEMS Cloud and Snow Detection via Deep Learning Techniques(preliminary result)

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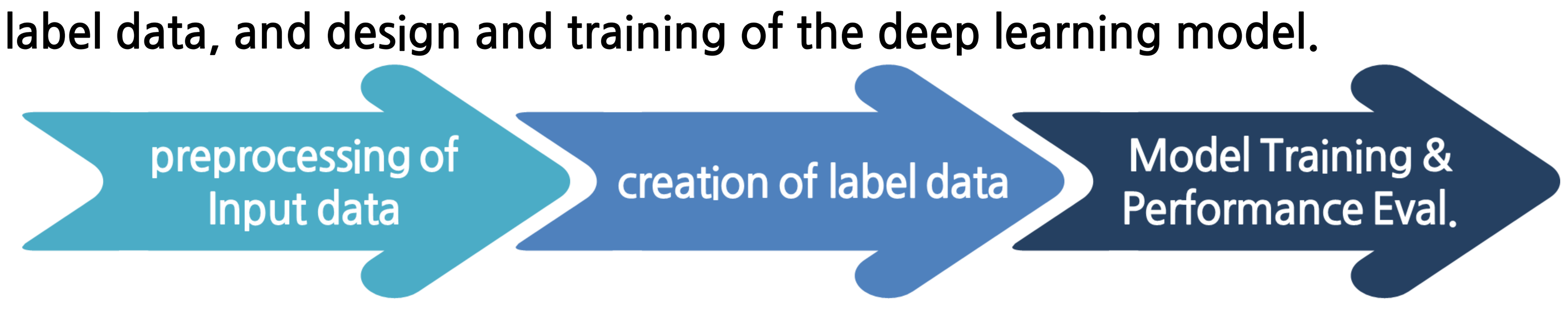
Introduction

The Geostationary Environment Monitoring Spectrometer (GEMS) captures images of the Asia region more than eight times a day, providing 21 key outputs related to air quality, which are crucial for analyzing and monitoring air quality in Asia. Accurate ground reflectance values are essential for deriving precise air quality outputs from satellite observations. However, errors induced by clouds and snow during the ground reflectance estimation process necessitate accurate identification of regions affected by these elements. Currently, GEMS detects clouds using absorption spectral data of O2-O2 and O3, which involves algorithms that calculate cloud cover based on differential absorption features. GEMS, unlike other environmental satellites that primarily utilize the visible light spectrum, predominantly uses the ultraviolet range, which has shorter wavelengths than visible light. This results in stronger interactions, such as scattering and absorption, with atmospheric particles. Consequently, compared to other environmental satellites that utilize the visible spectrum, GEMS exhibits relatively lower accuracy in deriving cloud coverage due to these interactions. For snow detection, GEMS relies on data from the Near-real-time Ice and Snow Extent (NISE) provided by the National Snow and Ice Data Center (NSIDC), rather than using a direct algorithm.

To address these issues, this study aims to improve the accuracy of cloud and snow detection by applying deep learning techniques, which have demonstrated superior performance in the field of image processing.

Methods

The research is divided into several parts: **preprocessing of input data, creation of label data, and design and training of the deep learning model.**



- Re-gridding Data
- Collapse bands
- Min-Max Normalization

- Selecting references Data
- Develop annotation criteria
- Perform labeling

- Build a Model
- Model training
- Performance Evaluation

Fig 1. Detailed workflow of this study.

The input data utilized the preprocessed data from GEMS's L1C. Since GEMS observes different areas depending on the time of acquisition, all data were gridded to the same area to align the observation areas uniformly. The intention was to utilize all 1,033 bands of GEMS for training the model. However, considering the complexity of the model and processing time, of the 1,033 bands, the last 1,024 bands were averaged in groups of eight to reduce them to 128 bands. Afterward, min-max normalization was applied to each of the 128 bands.

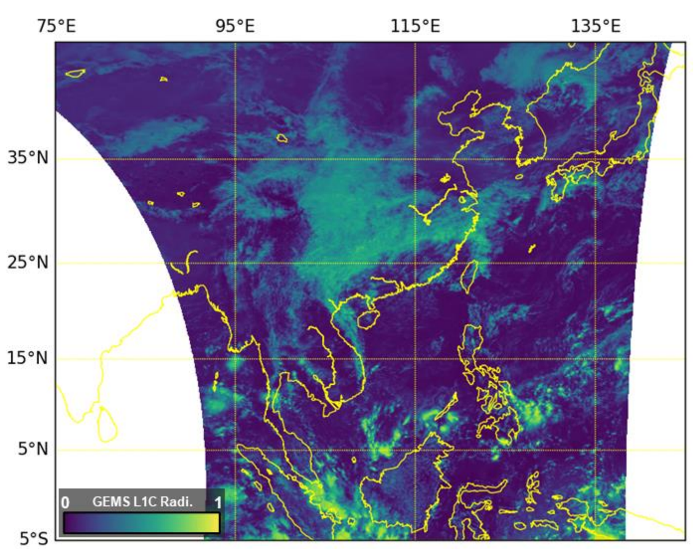


Fig 2. Example of Input Data.

Table 1. Properties of the Input Data.

Data Name	GEMS_CLD_yyyymmdd_hhmm.tif (yyyymmdd: Acquisition Date, hhmm: Time)
Area	Latitude: 5°S~ 45°N Longitude: 75°E ~ 145°E
Data Type	Float 32
Data Size	(1000, 1400, 128)

For the creation of label data, the following reference data were selected:

Table 2. Reference Data for Annotation(Labeling).

SNOW	Cloud
GEMS Snow flag (previous day's NISE product)	GEMS L2 Cloud data(ECF>=0.4)
Geo-KOMPSAT 2A(GK2A) AMI Snow data	AMI Cloud Data()
GK2A AMI Snow data quality flag(DQF)	False Color Image (average of GEMS Blue 450~500nm (Blue), AMI's NIR at 1.3 μm, AMI's SWIR).
MODIS Snow Cover Daily	
False Color Image (average of GEMS Blue 450~500nm (Blue), AMI's NIR at 1.6 μm, AMI's SWIR).	

Prior to the labeling process, an annotation guideline was created based on the selected reference data. This guideline included predefined methods and criteria for labeling, as well as quality control procedures. Following these guidelines, precise annotation work was conducted using QGIS.

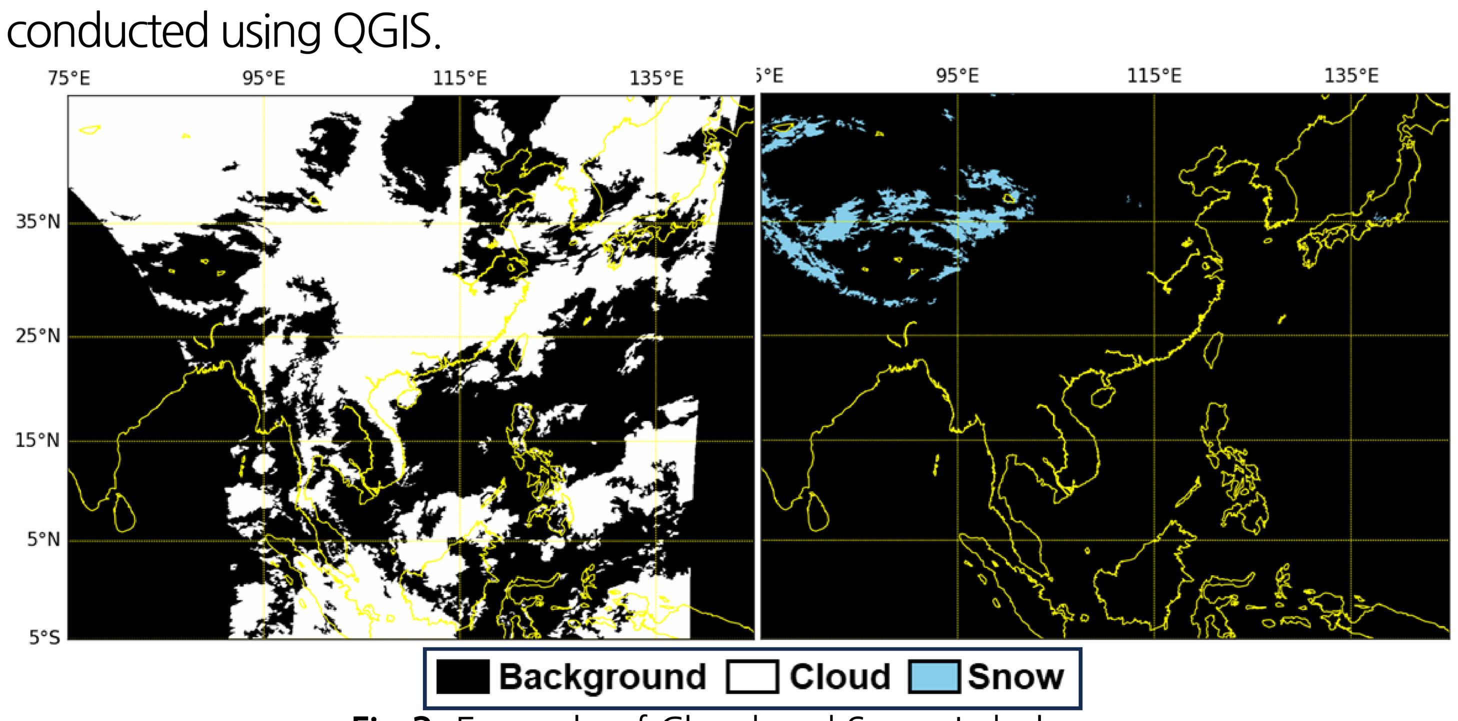


Fig 3. Example of Cloud and Snow Label.

The model training was conducted using preprocessed input data and the created label data. A total of **24 images** were used for snow detection, and **16 images** were used for cloud detection. Each piece of data was cut into 64 x 64 size patches for input into the deep learning model.

Subsequently, training was conducted using the **3D Attention U-Net**, designed for snow/cloud detection. Unlike the traditional U-Net, the 3D Attention U-Net utilizes 3D convolution operations instead of 2D convolutions, preventing the loss of channel information during the convolution process. Additionally, it employs an attention module that focuses on important features in both the spatial and channel dimensions, thereby enhancing the model's performance.

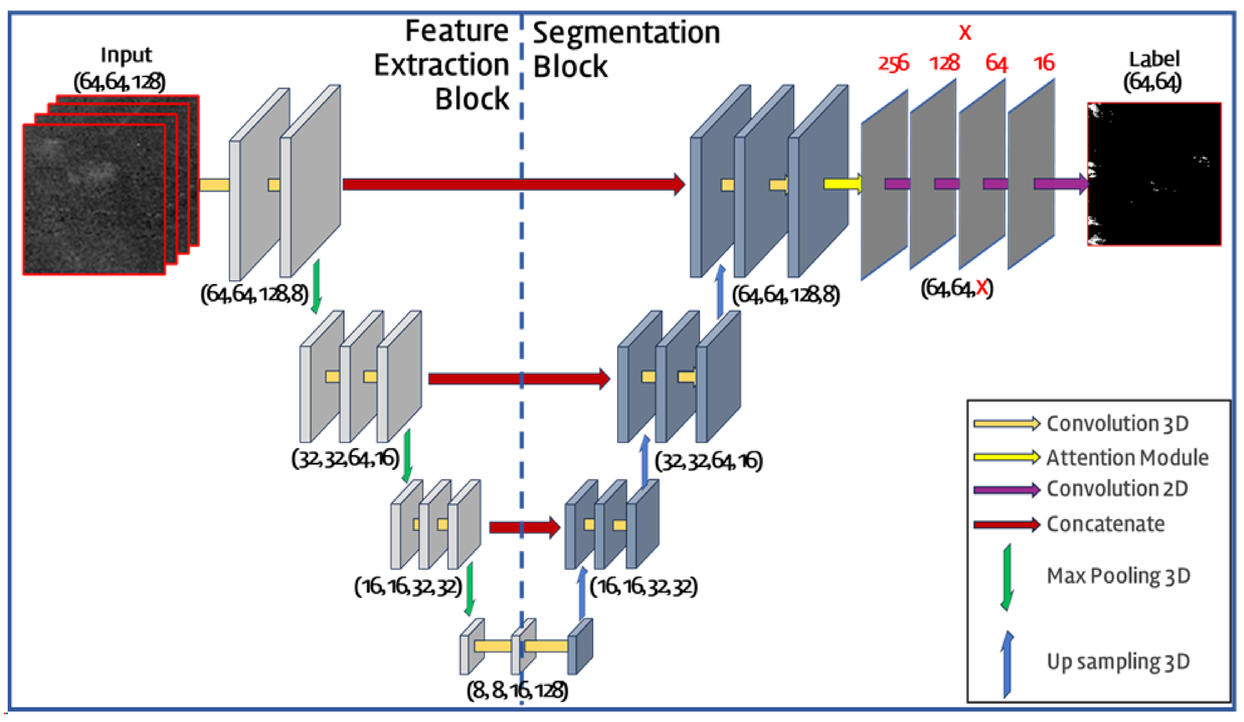


Fig 4. Model Structure of 3D Attention U-Net.

Table 3. Number of Patch Data.

Data Type		Number of Patch
Snow	Training	6,275
	Test	1,537
Cloud	Training	4,395
	Test	1,103

Table 4. Hyperparameter

Hyperparameter	Value
Optimizer	Adam
Learning Rate	1e-4 ~ 1e-5
Loss Function	Multi-Class Sparse IoU Loss
Batch Size	30
Epoch	300

Result

When evaluating the performance of the trained model using the test data, the results appeared as shown in the table below. Cloud detection showed high values, while snow detection displayed lower values. The relatively low performance in snow detection can be attributed to the fact that the data is from **early November 2021**. In the case of **clouds, the ratio of cloud to background pixels is nearly identical**, but the **snow-covered area pixels in the test data account for only 2.5% of the total pixels**. This comparison can also be observed through Fig.3.

Table 5. Performance Evaluation(Snow)

Indicator	Value
Precision	0.682
Recall	0.784
Accuracy	0.986
F1-Score	0.72
IoU	0.574

Table 6. Performance Evaluation(Cloud)

Indicator	Value
Precision	0.913
Recall	0.928
Accuracy	0.925
F1-Score	0.920
IoU	0.853

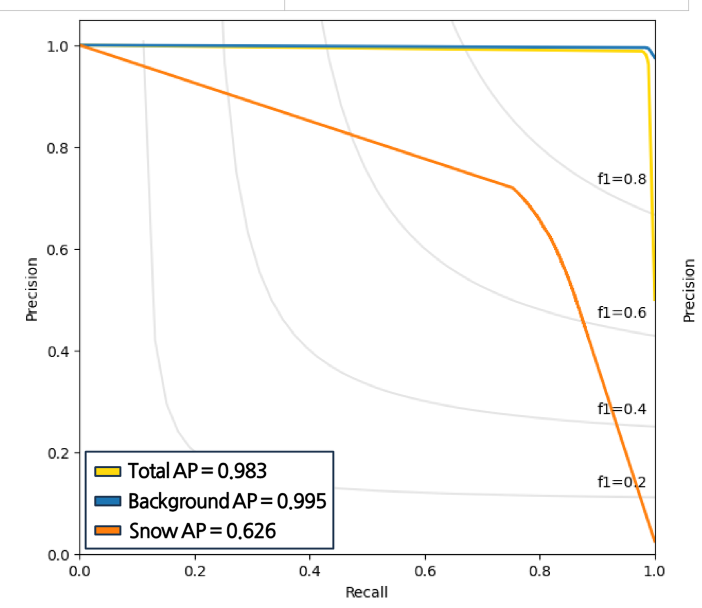


Fig 4. PR Curve(Snow)

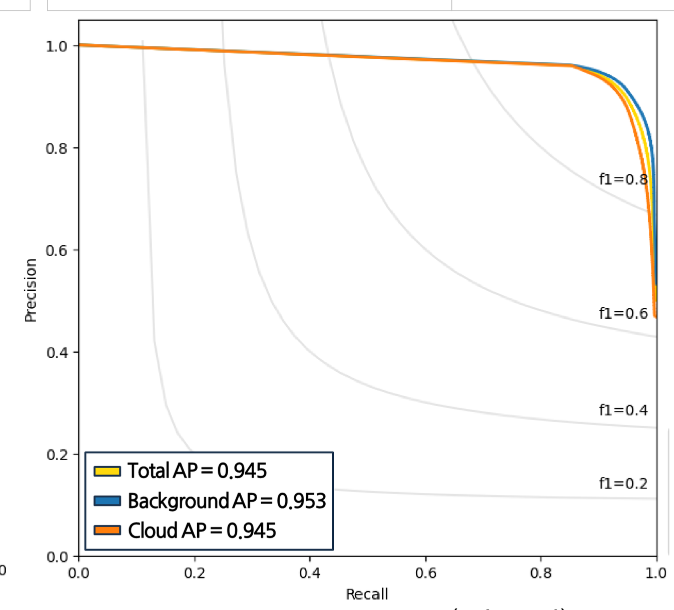


Fig 5. PR Curve(Cloud)

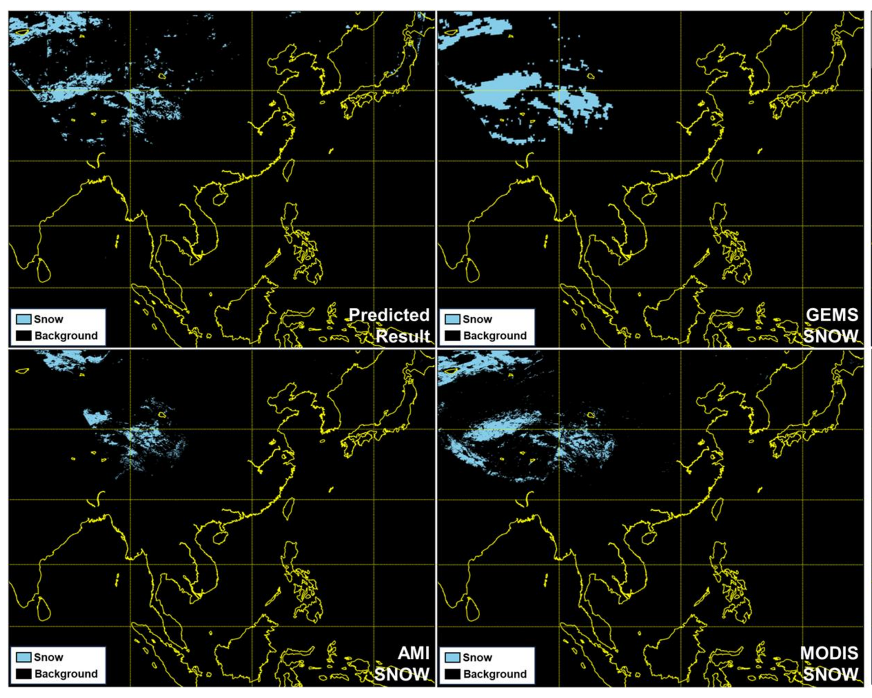


Fig 5. Predicted Result (Snow)

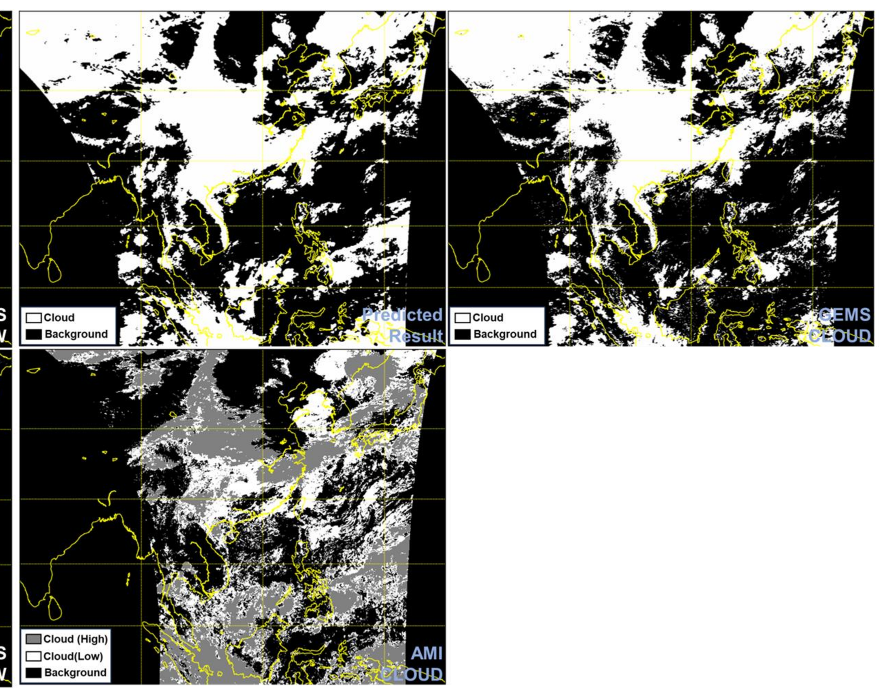


Fig 6. Predicted Result (Cloud)

Conclusions

In this study, deep learning techniques were applied to improve the snow/cloud output products of GEMS. The model's prediction results showed effective detection of cloud areas; however, the performance for clouds was relatively low. This was due to the use of imagery from early November, which contains a lower proportion of snow pixels, leading to a **data imbalancing** issue. Moving forward, **constructing label data for images from the snowier months** of December to January and **training the model with this data could enhance the performance of the snow products**.

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