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CLOUD TYPE CLASSIFICATION THROUGH SEMANTIC SEGMENTATION FOR ANALYSIS OF EARTH'S RADIATIVE BALANCE

Yu-Wen Wu[1], Nofel Lagrosas[2], Sheng-Hsiang Wang[3], and Albert Y. Chen[4]

1) Graduate Research Assistant, Department of Civil Engineering, National Taiwan University, Taipei, Taiwan. Email: r12521504@ntu.edu.tw
2) Assoc. Prof., Civil Engineering Department, Kyushu University, Fukuoka, Japan. Email: nofel@civil.kyushu-u.ac.jp
3) Professor, Department of Atmospheric Sciences, National Central University, Taoyuan, Taiwan. Email: carlo@g.ncu.edu.tw
4) Professor, Department of Civil Engineering, National Taiwan University, Taipei, Taiwan. Email: albertchen@ntu.edu.tw

Abstract: Classifying nighttime clouds is crucial for understanding their impact on earth's radiative balance. This study presents a semantic segmentation model using U-Net with a MobileNetV3 backbone for classification of the following cloud types: Cirrus, Nimbus, Stratus, and Cumulus from nighttime images. Despite challenges from reduced visibility at night, cloud types and coverage were effectively detected, classified and measured. The model results potentially facilitate future research on nighttime radiation analysis.

Keywords: Night clouds, Ground-based cloud images, Semantic segmentation model

1. INTRODUCTION

Clouds are visible masses of sparse liquid water droplets, ice crystals, or the mixture of both, suspended in the earth's atmosphere. Clouds form when water vapor in the air condenses or sublimates around microscopic particles, known as cloud condensation nuclei, in the atmosphere. This process occurs when air is cooled to its dew point or becomes saturated with moisture.

Clouds are classified based on their appearance, altitude, and the processes that lead to their formation. Cloud types play crucial role in the earth's weather and climate systems; clouds influence temperature, precipitation, and radiative balance by reflecting or trapping heat. Unlike daytime clouds, which are easily observed, nighttime clouds are more difficult to observe due to the absence of sunlight, making their classification challenging. Understanding nighttime clouds is essential to reasoning and quantifying, especially after sunset, how they influence surface temperatures by trapping or releasing heat, thereby affecting weather patterns. The ability to classify clouds enables for more accurate predictions of nighttime temperature variations and weather events, which can be useful in enhancing public safety and preparedness for sudden atmospheric changes. Adverse weather conditions, including cloud behavior, can significantly impact construction projects, affecting workforce productivity, supplier efficiency, and material damage, which in turn influence project timelines (Marzoughi et al., 2018). Ignoring the influence of weather can lead to project durations extending by 5–20% compared to planned schedules (Ballesteros-Pérez et al., 2017). Additionally, weather and radiative effects also impact surface temperatures of roads, subsequently affecting pavement conditions (Qin et al., 2022), urban structures, and the deterioration of bridges (Liu et al., 2022) and other infrastructure.

The significance of classifying nighttime clouds extends beyond immediate weather forecasting and into the realm of long-term climate studies. Nighttime clouds play a pivotal role in the earth's radiative balance, as they can either insulate the surface by trapping longwave radiation or allow cooling by permitting heat to escape into space. Accurately identifying these clouds can lead to refining climate models, helping researchers and modelers predict shifts in temperature, extreme weather, and the broader effects and changes of climate. Since clouds are a major source of uncertainty in climate modeling, a better understanding of their nighttime behavior can improve projections of atmospheric warming and other climate phenomena. This knowledge is critical for making informed decisions regarding climate adaptation and mitigation efforts, as well as for enhancing the accuracy of both weather and climate predictions.

2. LITERATURE REVIEW

Current research on cloud observation relies primarily on both satellite and ground-based observations. Satellite imagery offers convenient access to large-scale global atmospheric motion data at cloud tops. However, the limited resolution of these images often lacks required detailed local information. In contrast, ground-based cloud images provide more detailed regional information, which are particularly crucial for applications such as air traffic control. Additionally, ground-based observations tend to have lower data collection costs (Singh & Glennen, 2005). The types and amounts of clouds also significantly influence radiation and weather changes (Chen et al., 2000). Consequently, this study aims to achieve two main objectives: estimating cloud cover and recognizing cloud types.

To estimate cloud cover, the primary methods are divided into traditional thresholding techniques and deep learning approaches. Thresholding involves analyzing the differences in RGB or grayscale values between clouds and the background in an image, followed by applying a threshold to distinguish the two. Notable examples of this approach include adaptive thresholding that utilizes R-B or R/B ratios (Li et al., 2011) and conversion to grayscale cloud images that consider both visible and infrared light (Lagrosas et al., 2021). In contrast, deep learning approaches leverage architectures such as convolutional neural networks (CNNs) and U-Net (Ronneberger et al., 2015). These models take raw images as input to generate segmented images that effectively separate clouds from the background, as demonstrated in works such as CloudSegNet (Dev et al., 2019), SegCloud (Xie et al., 2020), and CloudU-Net (Shi et al., 2020).

For cloud type recognition, recent methodologies predominantly utilize deep neural networks. CNNs excel at capturing the shape and texture features of various cloud types (Ye et al., 2017), with some studies further classifying clouds into more distinct categories (Zhang et al., 2018). Techniques such as Bagging and AdaBoost have been shown to enhance classification accuracy (Zhang et al., 2020). However, this line of research often encounters challenges in accurately marking the coverage area of clouds and struggles when multiple cloud types are present in the same image (Ye et al., 2019).

Despite the advancements in i) cloud detection through image segmentation and ii) cloud recognition through image classification, there has been considerably less research that effectively combines these two approaches. One such method involves segmenting the image into superpixels before classifying them (Ye et al., 2019). More recent efforts have included end-to-end methods using encoder and decoder architectures (Ye et al., 2022) and a U-Net approach integrated with an attention mechanism (Shi et al., 2024). Notably, all these methods have primarily focused on daytime cloud datasets.

Overall, the advancement of deep learning models has significantly propelled research in cloud segmentation and classification. Nevertheless, there remains a notable gap in studies that address both tasks concurrently, particularly in relation to nighttime cloud datasets. Nighttime clouds are essential for understanding the earth's radiation balance, influencing both short-term weather and long-term climate. Therefore, this study aims to develop a deep learning-based semantic segmentation model for nighttime clouds to address this research gap. To this end, MobileNetV3 (Howard et al., 2019) will be utilized due to its small parameter size, rapid computation speed, and ability to maintain good accuracy, making it a suitable choice for constructing the model in this study.

3. METHOD

3.1 Overall Architecture

The architecture is based on U-Net, which is widely used for image segmentation. By taking a 416x320 ground cloud image as input, the U-Net performs feature extraction and up-sampling, ultimately producing an output of the same size that predicts which type of cloud each pixel belongs to, as shown in Figure 1. This allows for the estimation of area proportions of different cloud types, which serves as a basis for comparison with the observed radiation levels. The predicted cloud types include four categories: Cirrus, Nimbus, Stratus, and Cumulus, represented by red, green, blue, and yellow, respectively, in the final prediction image (along with black for the sky).

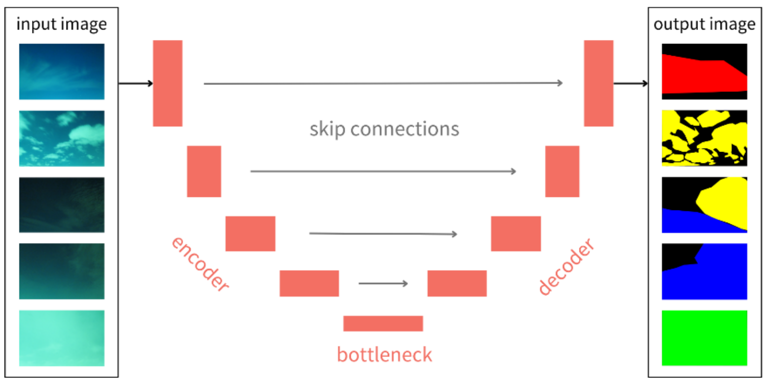


Figure 1. Framework of the cloud segmentation model

3.2 Model Configuration and Training Setup

The model employs a U-Net architecture with MobileNetV3 as the backbone. To enhance generalization, data augmentation was applied using a variety of transformations, including horizontal flip, vertical flip, grid distortion, random brightness-contrast adjustment, and Gaussian noise. The batch size is set to 4, and pretrained weights from ImageNet (Krizhevsky et al., 2012) were utilized to speed up model convergence, and fine tuning/transferring learning was conducted for 150 epochs of training. The optimization process uses the AdamW optimizer (Ilya Loshchilov & Frank Hutter, 2017) with a weight decay of 1e-4 to mitigate overfitting. The initial learning rate is set to 1e-3, and a cosine annealing scheduler (Ilya Loshchilov & Frank Hutter, 2016) is applied to dynamically adjust the learning rate during training, improving model performance.

Table 1. Training setup details

Parameter	**Details**
Model Architecture	U-Net with MobileNetV3 as the backbone
Data Augmentation	Horizontal Flip, Vertical Flip, Grid Distortion, Random Brightness-Contrast, Gaussian Noise
Batch Size	4
Pretrained Weights	ImageNet
Training Epochs	150
Optimizer	AdamW
Weight Decay	1e-4

Initial Learning Rate	1e-3
Learning Rate Scheduler	Cosine Annealing

3.3 Evaluation Metrics

The performance of the model is evaluated using several common metrics for segmentation tasks. First, cross entropy loss is employed as the loss function to measure the pixel-wise classification error between the predicted segmentation and the ground truth.

Additionally, pixel accuracy is utilized to assess the overall proportion of correctly classified pixels in the entire image, providing a general indication of the model's classification accuracy.

However, since pixel accuracy can be biased towards dominant classes in imbalanced datasets, the weighted Intersection over Union (wIoU) is also included as a complementary metric. The wIoU considers the intersection and union of the predicted and true segments for each class, using the proportion of each class in the ground truth as a weight, providing a more robust evaluation. The formula for wIoU is shown in Equation (1), where N is the total number of classes, and both i and j = {1, 2, 3, 4, 5}, corresponding to the five classes: Sky, Cirrus, Nimbus, Stratus, and Cumulus. GT refers to the number of ground truth pixels. TP, TN, FP, and FN refer to True Positive, True Negative, False Positive, and False Negative, respectively.

$$wIoU = \sum_{i=1}^{N} \frac{GT_i}{\sum_{j=1}^{N} GT_j} \cdot \frac{TP_i}{TP_i + FP_i + NP_i} \tag{1}$$

4. RESULTS

Data was collected with a Canon A2300 camera, programmed to continuously take nighttime sky images every 5 min at National Central University, Taiwan (24.97°N, 121.19°E). The infrared cut filter of the camera was manually removed so that the camera can function as an infrared camera. By doing this, a brighter image of the nighttime sky was observed. A total of 223 ground-based cloud images between 15 December 2021 to 19 February 2022 were then categorized into five types: Cirrus, Nimbus, Stratus, Cumulus, and Mix. Figure 2 depicts sample cloud images from the dataset.

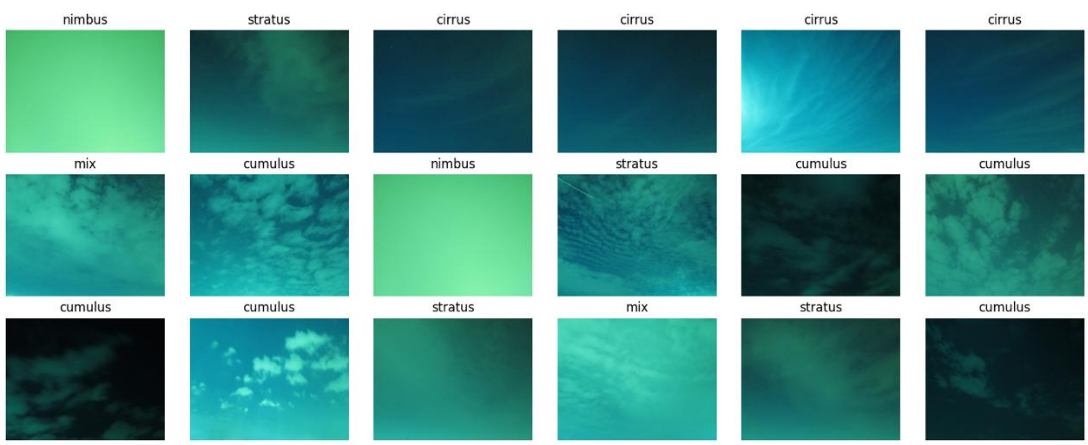


Figure 2. Sample cloud images from the dataset

To evaluate the model's performance, the dataset was split into training and validation sets with a 4:1 ratio. Additionally, to ensure the model's robustness, the proportion of different cloud types in both the training and validation sets was kept consistent. Table 2 shows the detailed information.

Table 2. Composition of training and validation datasets

Types	**Training Size**	**Validation Size**	**Total**
Cirrus	40	9	49
Nimbus	58	14	72
Stratus	24	5	29
Cumulus	43	10	53
Mix	16	4	20

Figure 3 illustrates the learning curves of the model throughout training, showing the progression of three key metrics: loss, average pixel accuracy, and average wIoU. All metrics exhibit a consistent improvement during the training process and gradually stabilize as they approach convergence. Notably, the validation curves for all metrics maintain a close alignment with the training curves, with the validation performance often surpassing the training results slightly. This indicates that the model not only avoids overfitting but also generalizes well, demonstrating strong robustness and the ability to perform effectively on unseen data.

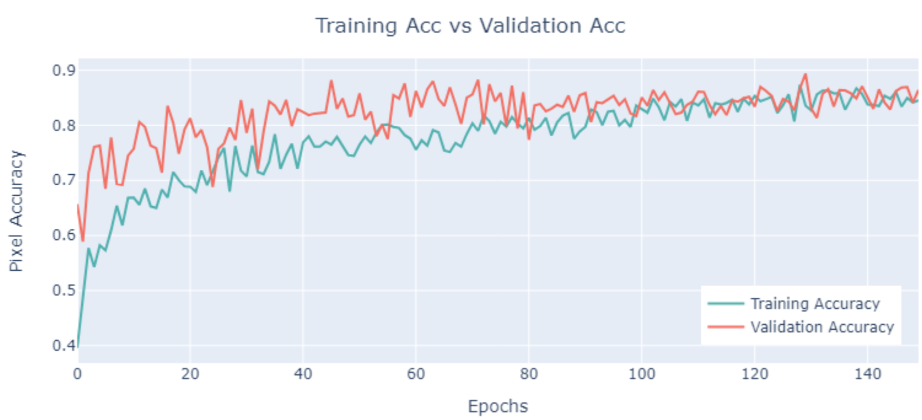
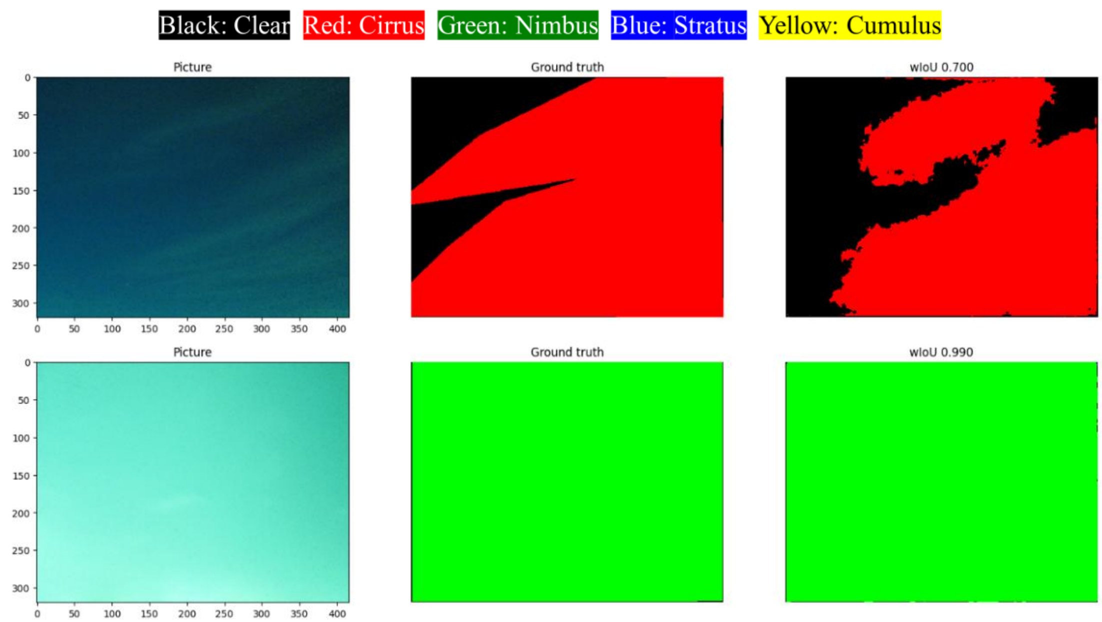


Figure 3. Learning curves of the model

The model with the lowest validation loss was selected as the final model, and some prediction results on the validation dataset are shown in Figure 4. These results indicate that the model not only performs well under ideal conditions but also exhibits robustness when confronted with challenging scenarios, such as thinner cloud layers and darker images. Table 3 provides a comprehensive overview of the final model's performance across different categories.



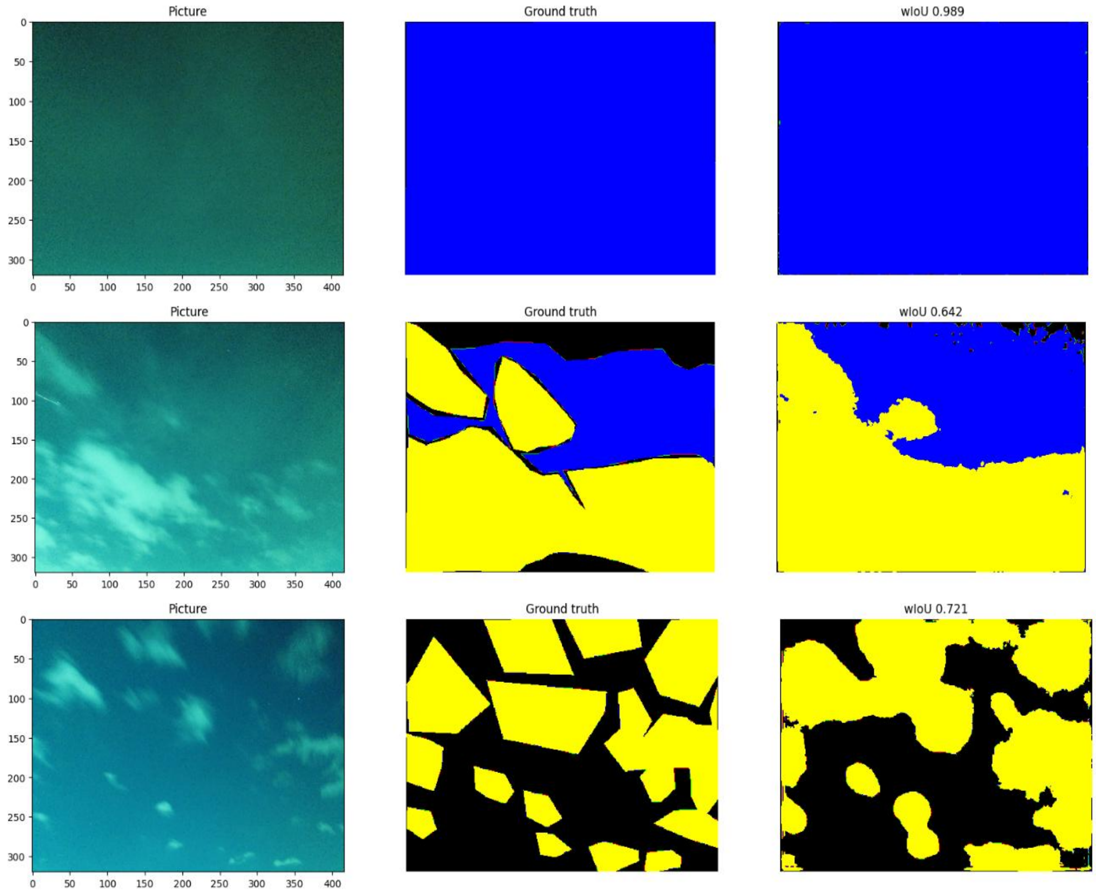


Figure 4. Some results on the validation dataset

Table 3. Final model performance on validation dataset

Types	Average Pixel Accuracy	Average wIoU
Cirrus	0.82	0.73
Nimbus	0.99	0.99
Stratus	0.97	0.96
Cumulus	0.87	0.84
Mix	0.64	0.47

The Cirrus cloud type presents a greater degree of variability, both in terms of its shape and the way it interacts with lighting conditions. This cloud formation often appears delicate and wispy, with significant differences in density and texture across different regions. Our prediction results, illustrated in Figure 5, demonstrate that the model has successfully identified and captured these nuances. The model was able to detect not only the denser, more prominent portions of the cloud but also the finer, more translucent areas. This highlights the model's ability to discern both subtle and obvious features within the cloud structure, showcasing its effectiveness in handling the complexity and variability inherent in Cirrus formation.

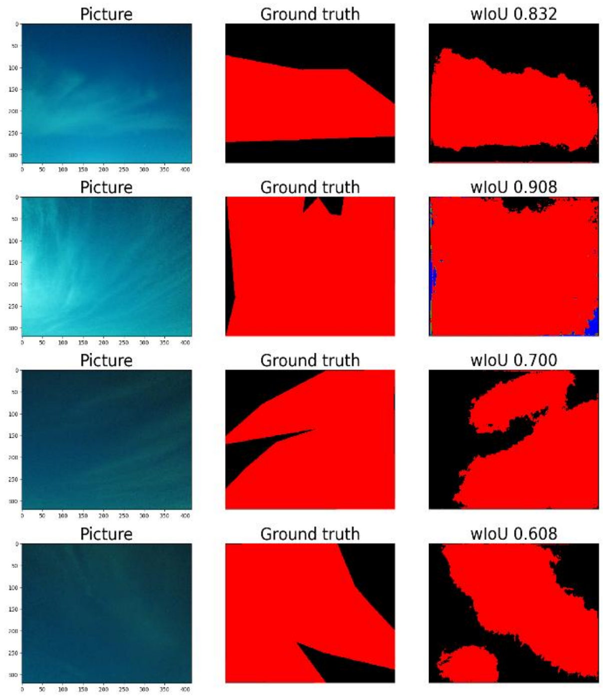


Figure 5. Cirrus cloud prediction results

The Nimbus cloud type, when present, typically cover the entire sky with their dense masses. This extensive coverage distinguishes Nimbus from other cloud types, which may appear more localized or scattered across the sky. Additionally, the color distribution in images containing Nimbus clouds is unique, as shown in Figure 6. This distinct color profile further sets them apart from other cloud formations, facilitating a more accurate classification of cloud types.

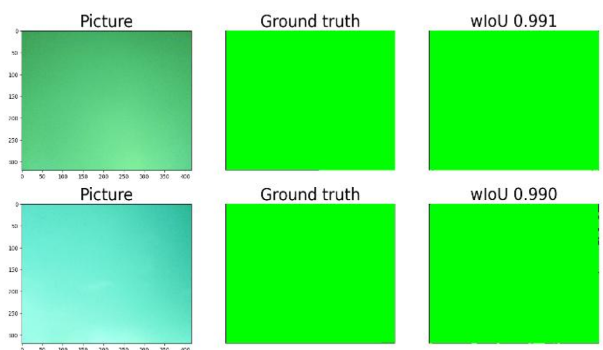


Figure 6. Nimbus cloud prediction results

Stratus clouds, when present, also typically cover the sky extensively (as shown in Figure 7), contributing to improved model accuracy. However, the model does not mistakenly classify entire images as Stratus clouds solely due to their presence. This refined behavior is particularly evident in the predictions for mixed cloud formations, as illustrated in Figure 9.

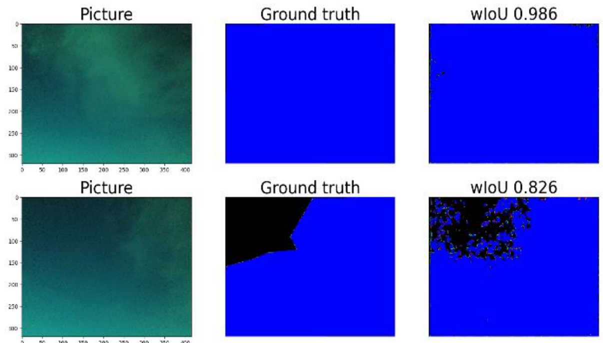


Figure 7. Stratus cloud prediction results

Cumulus clouds typically exhibit distinct shapes and bright white colors, making them ideal for model recognition. The results were promising, as expected, with the model performing consistently well across datasets with varying brightness levels.

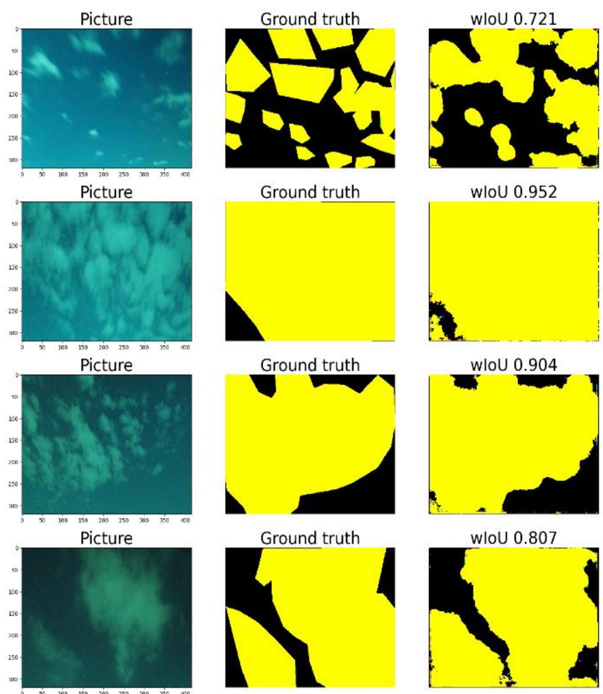


Figure 8. Cumulus cloud prediction results

In terms of predicting mixed cloud cover, we also achieved good results. This work demonstrates that it is possible to simultaneously perform cloud segmentation and classification for nighttime clouds, even when multiple types of clouds are present in the same image. However, there is still room for improvement in predicting images with very low brightness or extremely thin clouds, which makes our average pixel accuracy under the 'Mix' category look quite good, but the performance of the average wIoU is relatively poorer (as shown in Table 3). This will be one of the directions for future efforts.

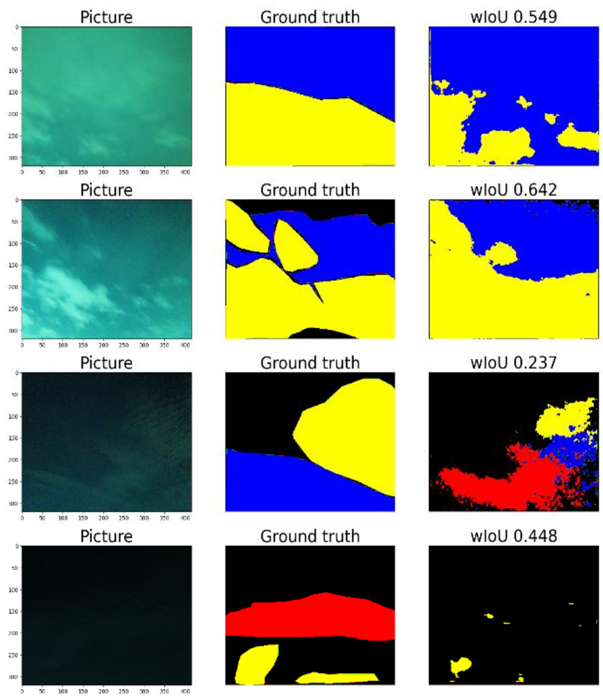


Figure 9. Mix cloud prediction results

To evaluate the effectiveness of the model, Table 4 presents a comparison of average pixel accuracy and average IoU with other studies. Although fewer categories were predicted, which will be one of the future improvement directions, the model still demonstrates good performance.

Table 4. Comparison with previous studies

Research	Predicted Categories	Acc	IoU
Ye et al., 2019	Sky, Cu, Sc, St, As, Ac, Cc, Cs, Ci	0.71	0.34
Ye et al., 2022	Sky, Cu, Sc, St, As, Ac, Cc, Cs, Ci	0.85	0.37
Shi et al., 2024	Sky, Cirrus, Stratus, Cumulus, Cumulonimbus & Laminatus	0.91	0.62
Ours	Sky, Cirrus, Nimbus, Stratus, Cumulus	0.86	0.80

5. CONCLUSION AND FUTURE WORKS

This study developed a deep learning-based semantic segmentation model to classify nighttime cloud types. The model demonstrated satisfactory accuracy and robustness across various cloud types, including Cirrus, Nimbus, Stratus, and Cumulus, showing promise for application in nighttime cloud monitoring. Notably, the model effectively managed challenges associated with low visibility at night, capturing essential cloud features and enabling further analysis of cloud type contributions to the earth's radiative balance.

Future work will address current model limitations, including detecting extremely low-brightness images in mixed clouds. Cloud types may also be further classified, such as dividing Stratus into Stratocumulus and Stratocirrus. Furthermore, the amount of net longwave radiation that can be attributed to each cloud type will be explored to understand the radiative effects of each cloud type.

This study is currently in the stage of understanding the science behind cloud classification before comparing the classified clouds with the longwave radiation measurements we have. While this requires processing a substantial amount of data, the ultimate goal has an engineering focus: to quantify how clouds influence nighttime environmental heating and rainfall and to explore the interrelationship between clouds and climate indices (e.g., La Nina, El Nino, AOI). The findings can significantly impact how engineers plan and mitigate disasters.

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REFERENCES

Ballesteros-Pérez, P., Rojas-Céspedes, Y. A., Hughes, W., Kabiri, S., Pellicer, E., Mora-Melià, D., & del Campo-Hitschfeld, M. L. (2017). Weather-wise: A weather-aware planning tool for improving construction productivity and dealing with claims. Automation in construction, 84, 81-95.

Chen, T., Rossow, W. B., & Zhang, Y. (2000). Radiative effects of cloud-type variations. Journal of climate, 13(1), 264-286.

Dev, S., Nautiyal, A., Lee, Y. H., & Winkler, S. (2019). CloudSegNet: A deep network for nychthemeron cloud image segmentation. IEEE Geoscience and Remote Sensing Letters, 16(12), 1814-1818.

Howard, A., Sandler, M., Chu, G., Chen, L. C., Chen, B., Tan, M., ... & Adam, H. (2019). Searching for mobilenetv3. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 1314-1324).

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, *25*.

Lagrosas, N., Shiina, T., & Kuze, H. (2021). Observations of nighttime clouds over Chiba, Japan, using digital cameras and satellite images. Journal of Geophysical Research: Atmospheres, 126(17), e2021JD034772.

Li, Q., Lu, W., & Yang, J. (2011). A hybrid thresholding algorithm for cloud detection on ground-based color images. Journal of atmospheric and oceanic technology, 28(10), 1286-1296.

Liu, K., & El-Gohary, N. (2022). Deep learning–based analytics of multisource heterogeneous bridge data for enhanced data-driven bridge deterioration prediction. Journal of Computing in Civil Engineering, 36(5), 04022023.

Loshchilov, I. (2017). Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*.

Loshchilov, I., & Hutter, F. (2016). Sgdr: Stochastic gradient descent with warm restarts. *arXiv preprint arXiv:1608.03983*.

Marzoughi, F., Arthanari, T., & Askarany, D. (2018). A decision support framework for estimating project duration under the impact of weather. Automation in Construction, 87, 287-296.

Qin, Y., Zhang, X., Tan, K., & Wang, J. (2022). A review on the influencing factors of pavement surface temperature. Environmental Science and Pollution Research, 29(45), 67659-67674.

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18 (pp. 234-241). Springer International Publishing.

Shi, C., Zhou, Y., Qiu, B., Guo, D., & Li, M. (2020). CloudU-Net: A deep convolutional neural network architecture for daytime and nighttime cloud images' segmentation. *IEEE Geoscience and Remote Sensing Letters*, *18*(10), 1688-1692.

Shi, C., Su, Z., Zhang, K., Xie, X., Zheng, X., Lu, Q., & Yang, J. (2024). CloudFU-Net: A Fine-grained Segmentation Method For Ground-based Cloud Images Based On An Improved Encoder-Decoder Structure. *IEEE Transactions on Geoscience and Remote Sensing*.

Singh, M., & Glennen, M. (2005). Automated ground-based cloud recognition. Pattern analysis and applications, 8, 258-271.

Xie, W., Liu, D., Yang, M., Chen, S., Wang, B., Wang, Z., ... & Zhang, C. (2020). SegCloud: A novel cloud image segmentation model using a deep convolutional neural network for ground-based all-sky-view camera observation. *Atmospheric Measurement Techniques*, *13*(4), 1953-1961.

Ye, L., Cao, Z., & Xiao, Y. (2017). DeepCloud: Ground-based cloud image categorization using deep convolutional features. *IEEE Transactions on Geoscience and Remote Sensing*, *55*(10), 5729-5740.

Ye, L., Cao, Z., Xiao, Y., & Yang, Z. (2019). Supervised fine-grained cloud detection and recognition in whole-sky images. *IEEE Transactions on Geoscience and Remote Sensing*, *57*(10), 7972-7985.

Ye, L., Cao, Z., Yang, Z., & Min, H. (2022). Ccad-net: A cascade cloud attribute discrimination network for cloud genera segmentation in whole-sky images. *IEEE Geoscience and Remote Sensing Letters*, *19*, 1-5.

Zhang, J., Liu, P., Zhang, F., & Song, Q. (2018). CloudNet: Ground-based cloud classification with deep convolutional neural network. *Geophysical Research Letters*, *45*(16), 8665-8672.

Zhang, J., Liu, P., Zhang, F., Iwabuchi, H., e Ayres, A. A. D. H., & De Albuquerque, V. H. C. (2020). Ensemble meteorological cloud classification meets internet of dependable and controllable things. *IEEE Internet of Things Journal*, *8*(5), 3323-3330.