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AI-based Segmentation Model for Aerial Imagery

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Abstract – **Advancements in artificial intelligence (AI) have facilitated the utilization of high-resolution aerial images, opening new avenues for a variety of applications. However, large-scale dataset with guaranteed diversity and data preprocessing may be mandatory for precisely identifying the region of interest in aerial images using AI. In this paper, the issues are addressed by applying a segmentation model to analyze aerial images for solar panel dataset (SPD) and solar potential installable area dataset (SPIAD). By employing data augmentation techniques and acquiring large-scale datasets, the study can navigate the inherent complexities of aerial images, thereby improving the accuracy of the outcomes.**

Index Terms –Artificial Intelligence, Aerial Imagery, Instance Segmentation, Solar Photovoltaic

1. INTRODUCTION

A rapid advancement of computer vision has led to utilization of high-resolution aerial images, providing an unprecedented opportunity for various applications such as reconnaissance, urban planning and analysis, environmental monitoring, and disaster management [1-3]. However, the effective utilization of aerial images has been required sophisticated analysis techniques. One such candidate technique that has gained significant attention is a segmentation model, a process of partitioning an image into distinct regions that correspond to interested objects or features [4].

Segmentation technique, a subfield of computer vision, has been extensively advanced by the advent of artificial intelligence (AI). AI-based segmentation models can automatically learn to recognize complex patterns in images, thereby significantly improving the accuracy and efficiency of sophisticated image analysis. However, there are a number of issues with employing AI-based segmentation for aerial image analysis. The issues may include variations in scale and orientation, a lack of large-scale benchmarks, and a diverse set of object categories [5-7]. The variations in scale and orientation are a characteristic of aerial images, where objects of interest are distributed in various directions and sizes. This is called the bird's eye view problem, and make it much harder to recognize objects in aerial images than in natural images [8]. The large-scale benchmarks with well-annotated datasets and the diverse set of object categories are essential to training robust AI models, but acquiring these datasets in aerial images requires substantial resources and time to collect and annotate accurately. Furthermore, the dynamic nature of aerial imagery, where the environment can vary considerably over time, makes it challenging to incorporate aerial images into AI models. These challenges highlight the need for robust algorithms and reproducible research in the field of AI-based aerial image analysis.

In this paper, aerial image analysis is performed for solar panel detection and identification of potential sites, while the aforementioned problems are mitigated. The detection of solar panels and the identification of potential sites for their installation, using aerial images, have emerged as significant areas of research in recent years [9-

11]. This trend is largely driven by the growing interest in renewable energy sources. However, the field is struggling with numerous issues. These include a scarcity of well-annotated datasets, which are essential for the development of robust AI models, and suboptimal performance in aerial image analysis stemming from the inherent complexities of aerial imagery. In this paper, the challenges inherent in AI-based aerial analysis can be overcome by the employment of data augmentation techniques and large-scale dataset acquisition. With the proposed methodology, it is confirmed that the complexities inherent in aerial images can be effectively navigated, leading to the acquisition of accurate and reliable results.

FIGURE 1

EXAMPLE OF ANNOTATIONS IN SPD.

The contributions of this paper are as follows:

- **Construction of Large-scale Training Data for Robust AI Model**: Large-scale datasets have been constructed for the purpose of training robust AI models that are capable of detecting solar panel and identifying potential sites. Diverse applications in renewable energy can be explored by the provided datasets, potentially leading to feature advancements.
- **Improvement of usability of AI Models by Diverse Data Acquisition**: The datasets constructed in this paper has an enhanced utility value because it includes elements not seen in other published datasets in related research domains. This finding underscores the importance of diverse data acquisition in AI-based aerial image analysis.
- **Alleviation of Bird's Eye View Problem in Aerial Images Using Data Augmentation**: An approach was proposed that leverages data augmentation to tackle the bird's eye view problem inherent in aerial images. It is confirmed that the performance of the AI-based segmentation model is improved through the proposed method.

The remainder of this paper is organized as follows: in Section 2 provides a description of the datasets used for detecting solar panels and potential sites, in addition to detailing the AI-based segmentation model used for aerial image analysis. Section 3 describes data augmentation for overcoming the bird's eye view problem. Section 4 is devoted to simulation setting, performance metrics, and results of simulation results. The conclusion of this paper is discussed in Section 5.

2. DATASET AND AI-BASED SEGMENTATION MODEL

Aerial images, particularly those captured by satellites and drones, have found extensive applications in various fields. These applications leverage AI to extract meaningful insights from aerial images. In this paper, the solar panel dataset (SPD) and solar potential installable area dataset (SPIAD) have been constructed to facilitate the analysis of AI-based solar panel detection and potential site identification for solar panel installation. The datasets were obtained from the National Geographic Information Institute (NGII) in South Korea and each dataset was comprised over 20,000 aerial images. Each aerial image has the same resolution of 0.25m/px and size of 512 x 512 pixels. AI-based segmentation task are performed through Mask R-CNN and U-Net.

I. Solar Panel Dataset

In the research on solar panel detection, a variety of datasets have been utilized to facilitate research and application [12-13]. The HyperionSolarNet dataset, which consists of aerial images, is specifically designed for detecting solar panels from aerial images and is used to train a two-branch model that includes an image classifier and a segmentation model [12]. In [13], dataset consisting of orthophoto was proposed to design an automated solar panel detection model. While the conventional datasets demonstrate capability in detecting solar panels, their effectiveness is constrained by small quantity of data and the diversity of scales. Consequently, these limitations hinder their utility for comprehensive analysis. In order to overcome the limitations of existing datasets, we have gathered and annotated 23,287 equal-sized aerial images containing solar panels. Due to the identical image size of the aerial images in the SPD, the scale of the solar panel installation can be estimated by computing the pixel value of the detected area from the AI model. Additionally, the collected aerial images can be utilized to create a robust AI model because the trained data encompasses diverse circumstances, such as buildings, land, and lake, allowing the AI model to train robustly. An example of an annotation of SPD is shown in Figure 1.

TABLE I

THE CHARACTERISTICS IN SPD AND SPIAD.

Dataset	Property	Number of Image	Relative (%)
SPD	Building	14,921	64.07
	Ground	8,271	35.52
	Lake	95	0.41
SPIAD	Top	12,164	52.01
	Roof	11,192	47.99

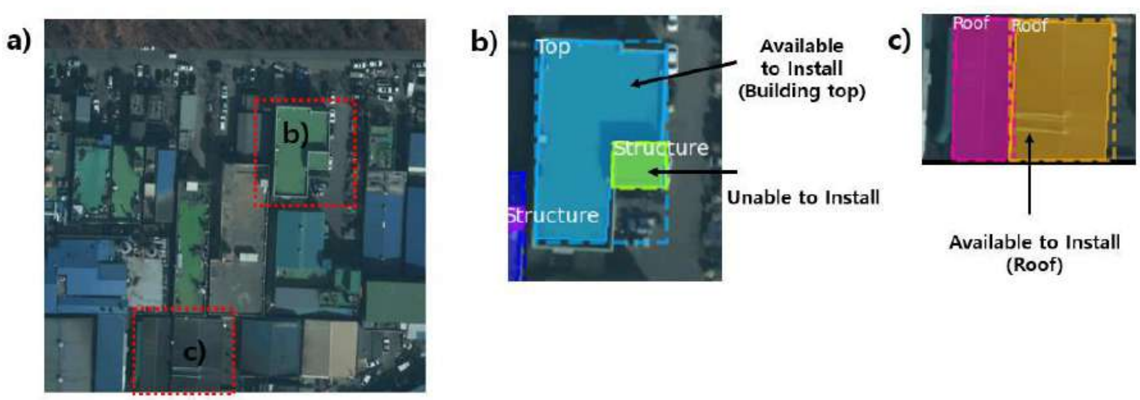

FIGURE 2

EXAMPLE OF ANNOTATIONS IN SPIAD. **(a)** RAW IMAGE SAMPLE;
(b) SEGMENTATION FOR BUILDING TOP AND STRUCTURE; **(c)** SEGMENTATION FOR STEEP ROOF.

II. Solar Potential Installable Area Dataset

In order to train AI models to locate solar panel installations automatically, datasets for solar potential analysis have been utilized. Existing datasets for solar potential analysis are the DeepRoof dataset and the roof information dataset (RID) [9]. However, these datasets, which consist of aerial images collected from a specific region, suffer from issues such as data imbalance and insufficient quantity. Additionally, both DeepRoof and RID are limited to residential houses, failing to reflect the demand for solar panel installation in buildings. In order to address these limitations, we created a large-scale data set called SPIAD which consists of 23,329 aerial images and takes into account both houses and buildings. Our dataset is available for download at AI-hub [14].

In SPIAD, objects that can accommodate solar panels are categorized as top and roof, where the top refers to the roof of a building and the roof refers to the roof of a residential house. This distinction is made because the available area for installing solar panels differs between building and residential house. Typically, a building roof can accommodate solar panels on 70% of the calculated area, while a residential gable roof can accommodate them on 100% of the calculated area. Additionally, in order to prevent the overestimation of the solar potential area from imagery, two factors were taken into consideration. Firstly, not all roofs and tops in the aerial imagery were deemed suitable for solar panel installations. It was determined that roofs and tops not exceeding $400m^2$ are unsuitable for solar panel installation due to the low power generation efficiency relative to the cost of solar panel installations for small-scale roof and top objects. The building area was calculated by referring to the building ledger, and buildings with an area of less than $400m^2$ were considered unsuitable for solar panel installation. Secondly, there are structures on building rooftops, such as rooftop gardens, elevator towers, facilities, ventilation towers, water tanks, and decorative towers, that do not permit solar panel installation. These objects were assigned a structure class because they may cause an overestimation of the solar potential as a whole. Figure 2 provides an example of how objects suitable for solar panel installation were labeled in the collected aerial images. The compositions of SPD and SPIAD are shown in Table 1.

III. AI-based Segmentation Model

With the advancements in computer vision and graphic processing unit (GPU), the primary focus of deep learning-based object detection has shifted toward segmentation models, which necessitate more computation than bounding box-detection models. Segmentation models are divided into semantic segmentation and instance segmentation.

The semantic segmentation is employed from object detection with object being to classify each pixel from an input image into a class. In semantic segmentation, all pixels within a specific segment are assigned the same class label, irrespective of whether they belong to different objects in the image. Segments of a particular class are assigned the same class label for the same distinguishable object in a single image. The semantic segmentation includes U-net, ReSeg, SegNet, and VGG-16. In contrast, the instance segmentation is utilized to identify and separate individual objects within an image. The aim of instance segmentation is to create a pixel-by-pixel segmentation map of an image, with each pixel being assigned to a specific object instance. This implies that each pixel belonging to a different object is given a different class label. The instance segmentation model includes models such as Mask R-CNN, DeepMask, and Mask-Lab. The outcomes of both semantic and instance segmentation applied to the SPIAD are represented in Figure 3. The U-net and Mask R-CNN models were employed as representative models for semantic segmentation and instance segmentation, respectively.

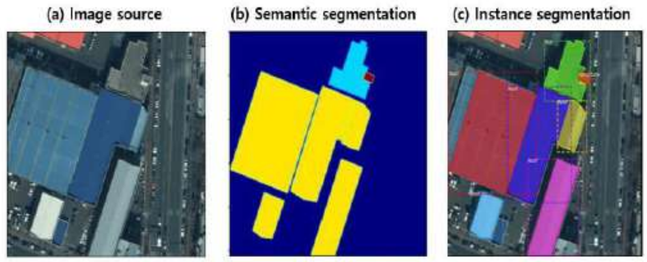

FIGURE 3
COMPARING SEMANTIC SEGMENTATION AND INSTANCE SEGMENTATION.

U-net was chosen as a representative model for semantic segmentation because of its efficiency. U-net architecture, which consists of a contracting path for encoder and an expanding path for the decoder, enables accurate localization of segmented objects and the extraction of features from the input image [15]. It makes U-net particularly suitable for handling complex backgrounds and multiple target instances often found in aerial images.

Mask R-CNN was selected as the representative model for instance segmentation due to its high usability. The architecture of Mask R-CNN allows for efficient object detection in an image and generates high-quality segmentation masks for each instance [16]. Furthermore, the versatility of Mask R-CNN, as demonstrated by its successful application in various types of objects within aerial images, ensures its adaptability to different use cases. Therefore, it is well-suited for instance segmentation tasks in our datasets.

3. DATA AUGMENTATION

Data augmentation has been utilized to generate additional data, thereby enhancing accuracy of deep learning models such as object detection, semantic segmentation, and instance segmentation. Conventional data augmentation methods, which apply the same transformations to all data, may not be suitable due to the specific characteristics of the data. Moreover, the manual selection and adjustment of augmentation rules can be time-consuming and labor intensive. In order to address these limitations, learning policies for data augmentation have been developed to automate the design of augmentation strategies. Using trained data augmentation in AI models has been used in a variety of fields as a way to significantly improve accuracy, robustness, and performance. However, the improved accuracy and model robustness offered by learned data augmentation policies with additional computational requirements and complex optimization procedures. In order to mitigate the complexity of the learned data augmentation policies, methods based on neural architecture search have been proposed. Although the method can minimize complexity, it still requires a separate search space, leading to the complexity of training AI-model and the computational cost.

In response, RandAugment has been proposed as a practical method for automated data augmentation. RandAugment randomly applies a sequence of predefined image transformations, such as rotation, translation, scaling, shearing, and color distortions, to augment the original images [17]. The process involves the selection of a specific number of augmentation operations from a predefined set, which are then applied sequentially to each image in the training dataset. The number of operations to apply is determined by a hyperparameter, "*N*". Each operation is randomly chosen and applied with a certain magnitude or strength, determined by another hyperparameter, "*M*". The magnitude controls the intensity of the transformations. By applying random combinations of transformations to the training dataset, the diversity of the training dataset can be increased. By employing the RandAugment to enhance the diversity of the dataset, it is possible to mitigate the bird's eye view problem inherent in aerial images, which is caused by variations in scale and orientation. RandAugment may make it possible to train AI model on aerial images in a more comprehensive and robust. Overall, an efficient and flexible approach to data augmentation is offered by RandAugment, enabling deep learning models to benefit from a larger and more diverse training dataset and simultaneously outperform in benchmark datasets.

Consequently, RandAugment is employed as a data augmentation method to efficiently improve the performance of the proposed model. Examples of the application of RandAugment are illustrated in Figure 4.

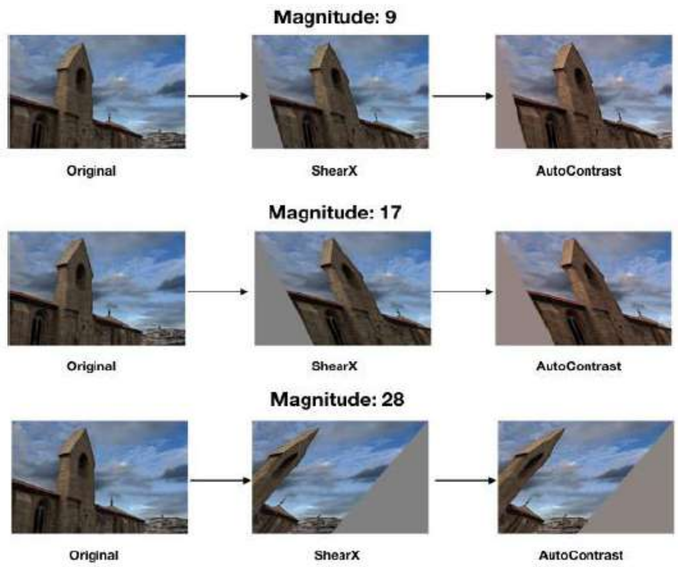

FIGURE 4

EXAMPLES OF APPLYING RANDAUGMENT.

4. SIMULATION RESULT

This section aims to evaluate the SPD and the SPIAD for segmentation models, and it is confirmed that the RandAugment technique affects the performance of AI-based aerial image analysis. In the training model, Stochastic Gradient Descent optimizer is used, with a learning rate of 0.001, 250 batch size. The deep learning model was trained for 500 epochs. Simulation results is verified through a test dataset. The simulation was executed in a PC with i9-10940X CPU, GeForce RTX 3090 GPU, and 64GB RAM.

I. Simulation Setup

For instance segmentation model training, the SPD and the SPIAD were partitioned into a training dataset (80%), a validation dataset (10%), and a test dataset (10%), respectively. RandAugment was performed on the training dataset. In RandAugment, the hyperparameters (*N, M*) were optimized using a grid search method, which systematically inputs specified values to identify the hyperparameters that yield the highest performance. The specific hyperparameter values and augmentation types for each model are detailed in Table II.

TABLE II

HYPERPARAMETER VALUES AND AUGMENTATION TYPES IN SIMULATION.

Datasets	**Instance Segmentation**	**Hyperparameter**		**Type of Augmentation**
		N	*M*	
SPD	U-net	1	9	Translate-x, Translate-y, Shear-x, shear-
	Mask R-CNN	2	4	

	U-net	1	7	y, Rotate, Invert, Cutout, Equalize, Solarize, Sharpen, Identify
SPIAD	Mask R-CNN	2	8	

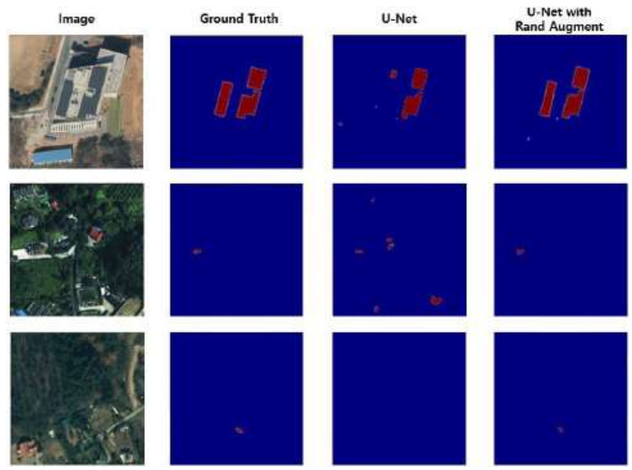

FIGURE 5
SIMULATION RESULTS OF U-NET FOR SPD.

II. Performance Metrics

Instance segmentation model can be evaluated by various aspects, including quantitative accuracy, visual quality, learning time, and storage requirements. The primary focus of application in AI-based segmentation is on metrics that quantify model accuracy. The performance of the instance segmentation with SDI and SPIAD is evaluated using the following metrics: mean intersection over union (mIoU) and mean average precision (mAP).

The mIoU, referred to as the Jaccard index, is a metric employed to calculate the similarities between the ground truth and the predicted results from the model. The mAP serves as a metric in image segmentation, quantifying the accuracy of model in predicting both the location and boundaries of objects within image. It is calculated by taking the average of precision values that were acquired at various recall thresholds.

III. Segmentation Results for SPD and SPIAD

Figure 5 shows the outcomes generated by U-net, when tested with the SPD dataset. When it comes to training the model, U-net refers to the case where RandAugment technique is not applied. Based on the simulation results, it was confirmed that objects resembling solar panels were erroneously detected in U-net. Conversely, when RandAugment was incorporated during the model training, the detection of solar panels was found to align closely with the ground truth.

Figure 6 presents the outcomes of the SPD dataset using Mask R-CNN, an instance segmentation model. In contrast semantic segmentation, the capability to identifying the same object as distinct entities is possessed by instance segmentation. From simulation results, it was showed that the performance of the instance segmentation model can be enhanced when the RandAugment technique is employed, which is similar to results obtained with U-net.

Figure 7 and 8 show the learning results of the SPIAD dataset using U-net and Mask R-CNN, respectively.

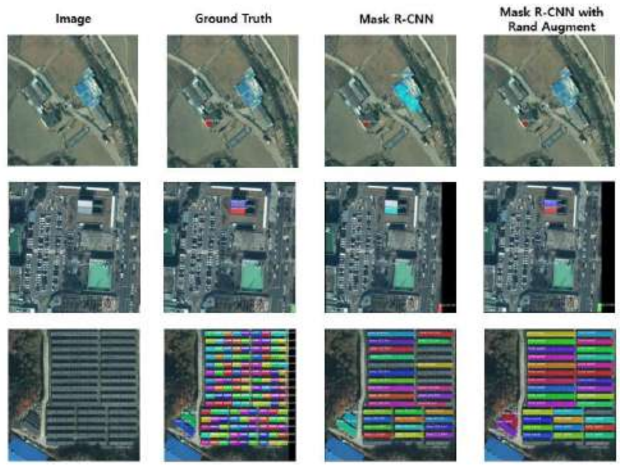

FIGURE 6
SIMULATION RESULTS OF MASK R-CNN FOR SPD.

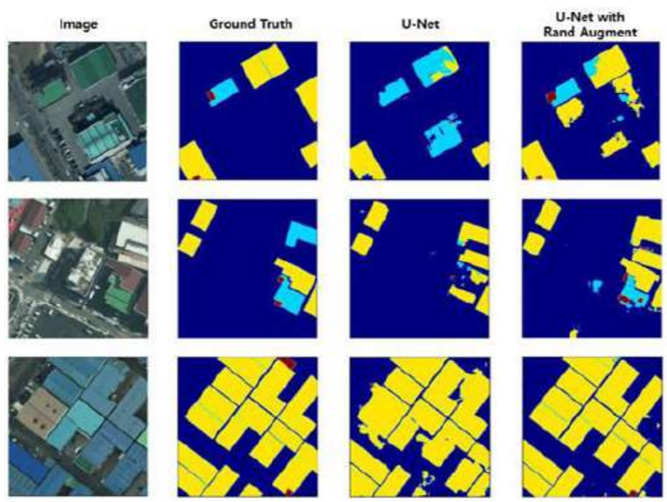

FIGURE 7
SIMULATION RESULTS OF U-NET FOR SPIAD.

Encompasses a large number of objects that need to be detected, and these objects exhibit a greater diversity in terms of their color characteristics. In the SPIAD dataset, it was confirmed that the employment of the RandAugment technique enables the learning model to enhance detection performance outcomes that closely approximate those of the ground truth.

With respect to the simulation results in Table III, which represent the evaluation of the SPD and SPIAD on the test dataset, it is noteworthy that the RandAugment technique can provide improved performance in the aerial image analysis through a segmentation model. The simulation results highlight the potential efficiency of RandAugment as a robust tool for enhancing the precision of aerial image segmentation tasks. This provides valuable insight into the advancement of AI-based aerial image segmentation model.

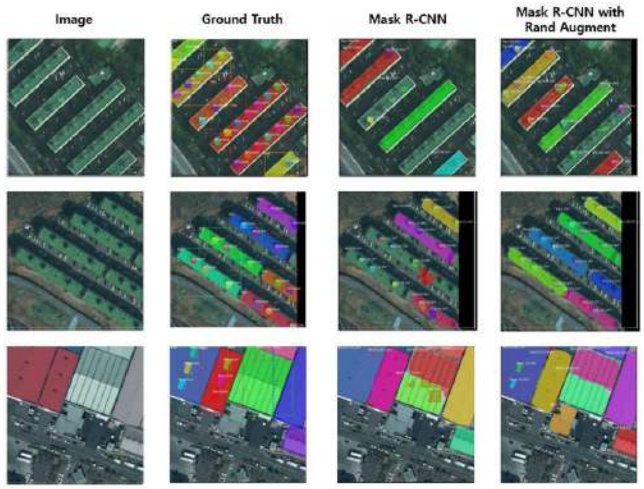

FIGURE 8
SIMULATION RESULTS OF MASK R-CNN FOR SPIAD.

TABLE III
SUMMARY OF SIMULATION RESULTS FOR SPD AND SPIAD.

Dataset	Segmentation Model	Performance Metrics	Value (%)
SPD	U-net	mIoU	78.1
	U-net with RandAugment	mIoU	84.5
	Mask R-CNN	AP	85.2
	Mask R-CNN with RandAugment	AP	90.5
SPIAD	U-net	mIoU	60.2
	U-net with RandAugment	mIoU	67.3
	Mask R-CNN	mAP	58.6
	Mask R-CNN with RandAugment	mAP	70.2

5. CONCLUSIONS

In this paper, the exploration of AI-based segmentation models in the analysis of aerial imagery was conducted, with a focus on the challenges and solutions in solar panels detection and potential site identification.

Simulation results highlight the effectiveness of RandAugment in enhancing the performance of AI-based aerial image analysis. Both U-net and Mask R-CNN models, when trained with RandAugment, show notable improvements in mIoU and mAP. The results highlight the importance of large and diverse datasets, coupled with sophisticated data augmentation techniques, in achieving accurate and reliable results in the field of AI-based aerial image analysis.

This research can contribute to valuable insights into the importance of data augmentation and diverse datasets in enhancing the accuracy of AI-based segmentation models for aerial image analysis. Future research endeavors are expected to focus on developing more efficient data augmentation methods and models with high accuracy.

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