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The Study on Image-based water level recognition by using Deep Learning

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Abstract: In recent times, water level monitoring stations have been established on major rivers to detect changes in water levels. When the water level reaches a certain threshold, relevant units are alerted, and appropriate measures, such as the closure of bridges and roads, are taken. However, with the significant advancements in the field of AI image recognition, researchers are exploring the use of image recognition through CCTV images to monitor water levels more intuitively and potentially replace traditional water levels gauges, such as radar or pressure-based gauges.

This study employs deep learning techniques, specifically the current image segmentation of deep image learning, to segment water surface images captured by CCTV cameras. A virtual water ruler, drawn by the user, is then used to calculate the water level height by converting the intersection of the water surface and the virtual water ruler. The Deeplab V3 algorithm provided by Google was used to obtain 500 images in the demonstration area during morning, noon, and evening periods, with water level recognition performed every minute.

The accuracy rate of the water level detection by this study was calculated separately for morning, afternoon, and evening periods, resulting in an overall accuracy rate of 83.5%. These findings demonstrate that the image recognition method is a viable and effective replacement for traditional IoT devices. The sponsored water level recognition project, located next to the Lansheng Bridge in Wulai District, New Taipei City, was used as an example to showcase the potential applications of this technology in the field of water resource management.

Keywords: deep learning, river water level, CCTV

I. Introduction

With the water soaring during torrential rain, some bridges and roads must be closed. Therefore, it is essential to observe the relative water level at bridges. Radar wave and pressure water level gauges can be used to keep the water level. However, the maintenance cost of these two instruments is increasing year by year, and the sensing value of the instruments might be abnormal, causing the disaster prevention unit to be unable to judge the local situation effectively. Thus, it is necessary to use CCTV Cameras to understand the actual situation. This study hopes to find the water level line through the image recognition of river water level and to calculate the water level height through the method of virtual water ruler to achieve future warnings.

There are two kinds of literature discussing the current CNN image recognition. Yan-De Li(2018) used the algorithm to point out, “The difference between the predicted value and the actual value is less than 5 pixels (about 10 cm) as the accurate range, and the accuracy of water level identification within the accurate range is 98.2%”. In another article, Punyanuch (2020) focused on the accuracy of river identification in Japan, and the conclusion is 93% accuracy when using one camera while 75.6% accuracy of using multi-cameras. Both of these two articles classify images of water levels by object recognition method. The water level height can be calculated according to the current image-matching process. This project uses Image Segmentation instead of image classification. It will try to find the water level line and then match the water level line on the image by drawing a virtual water level to calculate the actual water level height. This study uses Image Segmentation instead of image classification to find the water level line and then to match the water level line on the image to draw a virtual water level for the calculation to see the actual water level height.

In terms of research methods, this research hopes to compare and analyze the Google Deepak model and the HRNetV2+OCR model to identify the water level line through the current well-known model and finally to analyze the results through the accuracy comparison, which can be practically applied to recognize various river water levels in the future.

II. Materials And Methods

2.1 Proposed Method

In this study, the water level identification is carried out in the Wulai area of Taiwan, a tourist attraction. When the typhoon and heavy rain came, the situation of closing bridges and roads occurred.

First, we collected about 800 images during the day, evening, and night. Each print will draw the water surface in the area and establish a training dataset by searching for two photos with high MIOU accuracy in recent years. Finally, we use various algorithms for training, taking 100 of them for verification and then calculating the loss rate.

In addition, we prepared about 50 test data sets for empirical comparison. Then we used the virtual water ruler drawn on the picture to find the intersection of the water surface line and the virtual water ruler to calculate the actual water level for future practice.

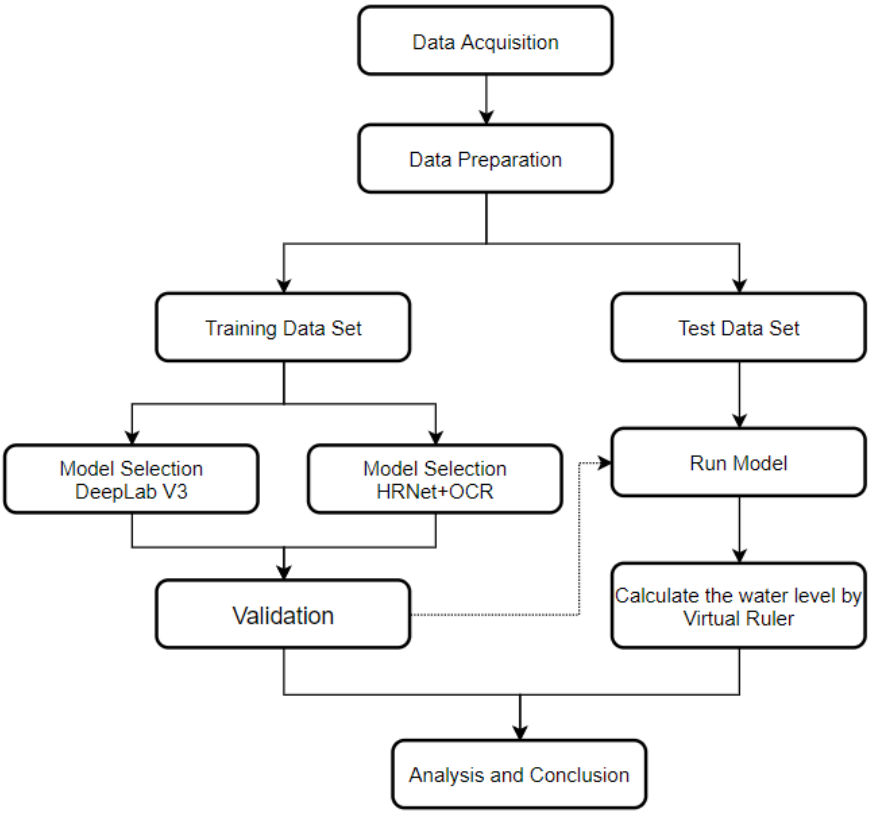

Fig 1. The overview of the proposed framework.

2.2 Model Selection

Semantic segmentation is an essential guideline for identifying water surface images. It can integrate standard models (including comparative deep learning models) and network architectures (including comparative network architectures) applied to the flooded road. The models include PSPNet, DeepLab, DANet, CFNet, etc., and network architectures cover VGG16, Inception, ResNet, and Xception. On the other hand, water-related texture features (ripples, splashes, raindrops, etc.) of the detection target can also be summarized. The texture feature is a situational feature to describe the surface properties of the scene corresponding to an image or its area. Texture cannot reflect an object's essential properties because it is its surface property, and its features are often affected by several factors. When the resolution of the image changes, the texture features will have a relatively large deviation, which is also affected by the lighting or reflection. Many kinds of literature use the complete connection condition to randomly obtain the texture feature correlation.

To know more accurately and apply models to surface models and architectures quickly, the score of each model becomes the secondary standard for reference. The scoring method is also called mean intersection over union (MIoU). The higher the score is, the more accurate the model will be.

The literature test samples considering the speed, accuracy, and model, are more in line with the actual interface image. Our team decided to use a proficient model which has been compared with MIoU. We adopted three models for analysis and comparison: the second model with DeepLab as the central axis and the

HRNetV2+OCR model. Figure 2-5 is a line graph of MIoU for each semantic segmentation model in recent years.

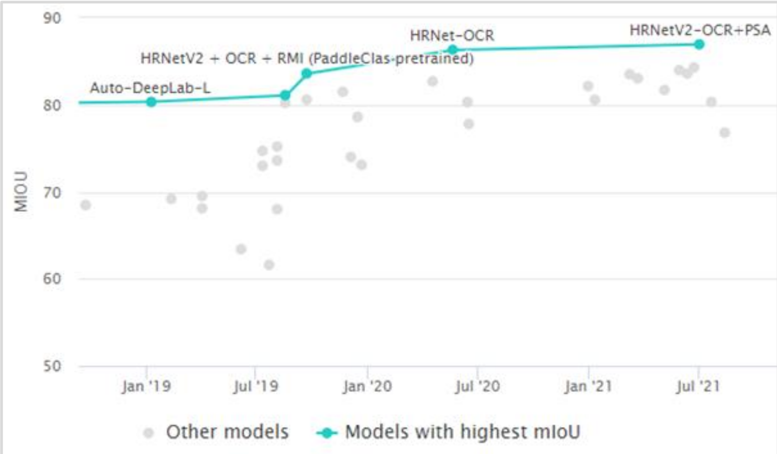

Fig 2. Image Segmentation Comparison with mIoUIndex (Source: https://paperswithcode.com/sota/semantic-segmentation-on-cityscapes-val)

2.3 Validation

To meet the actual model identification status, 100 images are reserved for verification, and the precise identification results determine the model to be applied to calculate the water level value. For DeepLabv3+ (Xception71 network) and HRNetV2-OCR (people label Ground Truth), the accuracy of the water level found by these two models is similar. In this study, it is located in the loss diagrams of each model (Figure 2-20) that in the same training sample, the training loss of DeepLabV3+ is faster and lower than that of HRNetV2+ OCR, so it is judged that DeepLabV3+ is more suitable for flooded areas.

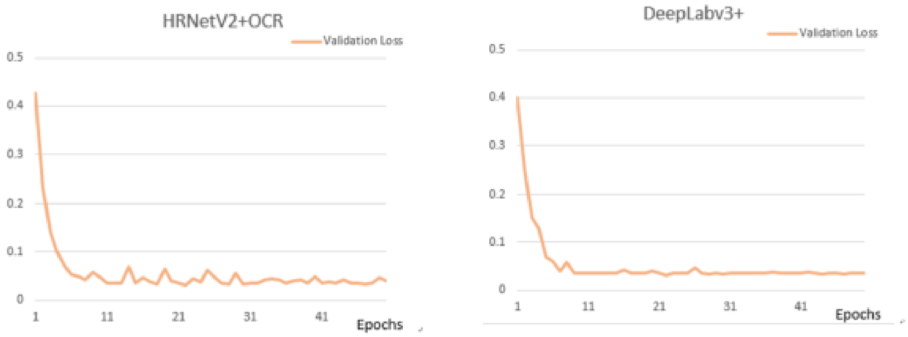

Fig 3. Loss diagrams with mIoU Index.

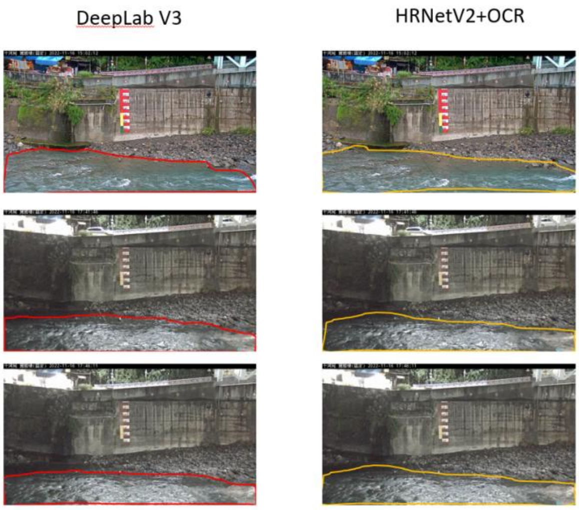

Fig 4.DeepLab V3 vs. HRNetV2+OCR (image recognition)

Volume – 08, Issue – 04, April 2023, PP – 14-17

III. Results and Discussion

3.1 Model Test

Based on the current 50 images and 1024*768 pixel of the identification size for calculation, its PA, MPA, MIOU accuracy indicators are as follows:

Table 1. Table layout. Captions for Tables are placed above.

Model	PA	MPA	MIOU
DeepLab V3	0.861	0.859	0.848
HRNetV2+OCR	0.848	0.835	0.821

3.2. Analysis and calculate the water level by Virtual Ruler

The following picture shows the water level height calculated by identifying the water surface range and a virtual water ruler. Accurate water surface recognition is used to assist in calculating the water level height, which is an effective method to replace the sensor. With the introduction of edge-operated cameras, this technology is believed to be widely used.

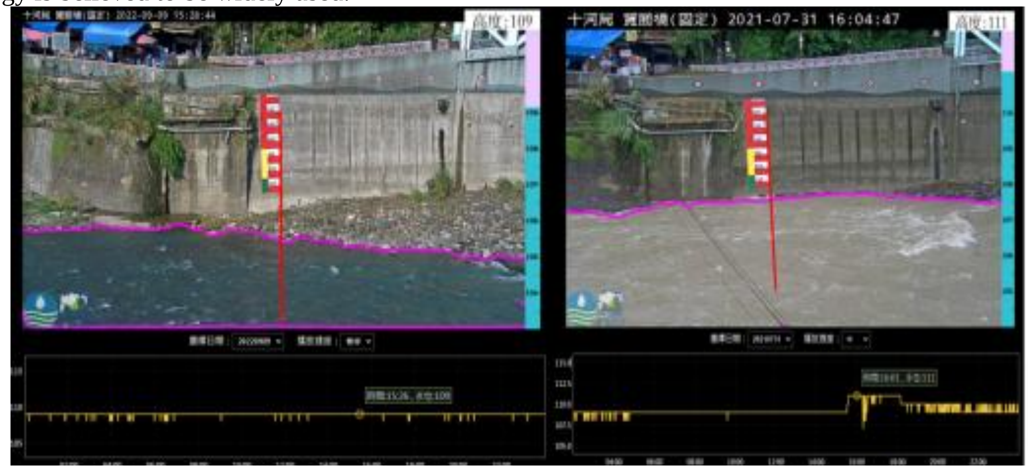

Fig 5. River Stage Detection

IV. Conclusions

4.1 Conclusion: This study hopes further to calculate the water level height through surface image recognition. Therefore, the ability of water surface image recognition is very important. The accuracy of the recognition in this study is over 83.5%, which can meet the demand for water level height to a certain extent in practice. In the future, we will continue to optimize and explore the technology of obtaining training samples automatically for using cameras with deep learning.

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