Research on aggregate grading based on deep learning

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ABSTRACT

Aggregate grading is an important link in aggregate production. Aiming at solving the problems of low efficiency of traditional artificial quality detection method and the detection accuracy affected by the subjective consciousness of the tester, combined with the method of deep learning, the intelligent grading of aggregates is realized in this paper. According to the aggregate provided by the local gravel company, 200 digital images of aggregate were taken and marked. Using FCN, DeepLabv3+, Attention-UNet, DANet, PSPNet to achieve the segmentation of aggregates. The particle size of the aggregate is calculated by drawing the minimum circumscribed circle of the aggregate, and then the aggregate is classified. The experimental results show that the method combined with deep learning has an accuracy rate of more than 95% in aggregate detection, and can accurately measure the particle size of aggregates, which is of great significance to the intelligent development of the industry.

Keywords: Aggregate grading, intelligent classification, deep learning, minimum circumscribing circle

1. INTRODUCTION

Concrete plays an important role in construction projects such as bridges and water conservancy[1], and sand aggregate is an important raw material for concrete[2, 3]. In practical engineering applications, aggregates are usually graded. Through aggregate gradation, small particles can fill the gap between large particles to achieve the purpose of saving cement. At the same time, the internal force distribution of the aggregate is improved because the contact point between aggregate particles is increased[4, 5]. Good aggregate gradation can save materials and improve the strength of concrete. If aggregate gradation does not meet the standard, the durability of concrete will be affected to a large extent[6, 7]. Therefore, accurate classification of aggregate is very important before aggregate grading.

At present, aggregate gradation is mainly carried out by a screening method, which requires manual measurement and screening of aggregate. This method requires a lot of human resources, low efficiency, and the detection accuracy is affected by the subjective consciousness of the tester. With the development of artificial intelligence technology, digital image processing technology has been gradually applied in the field of building materials[8, 9]. Wei[10] designed an online detection system for ore material gradation, which calculated aggregate gradation by minimum boundary calculation and dimension feature extraction. Hamzeloo[11] estimated the particle size distribution of ores on the industrial conveyor belt by using a neural network, and found that the maximum inner circle was the most suitable method to characterize the particle size. Fan[12] extracted information from five perspectives for aggregate in the process of particle falling, proposed an equivalent volume characterization method of aggregate, and converted aggregate volume into mass through the least square method, thus realizing aggregate gradation more efficiently. Wang[13] proposed a deep learning based concrete aggregate segmentation method and added a compression and excitation module in ResNeXt50 to improve feature extraction efficiency. Combined with the deep learning algorithm, this paper constructs the intelligent grading system of aggregate, calculates the minimum circumscribed circle diameter of aggregate while detecting the aggregate, and realizes the accurate grading of aggregate.

2. MODELS

Image segmentation technology is involved in the field of unmanned driving, medicine and geological detection.

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Traditional image segmentation techniques include threshold segmentation[14-15], clustering segmentation algorithm[16-17], edge detection algorithm[18-19], etc. With the proposal of FCN in 2015, many neural network-based semantic segmentation techniques began to appear. In this paper, the FCN model[20], the PSPNet model[21], the DeepLabv3+ model[22], the Attention-UNet model[23], and the DANet model[24] are used to achieve semantic segmentation.

FCN builds an end-to-end semantic segmentation network, which uses convolutional neural network (CNN) for feature extraction, replaces the original fully connected layer in CNN with convolutional layer, and finally restores the feature map through transposed convolution to the original size. The FCN model structure is shown in Figure 1.

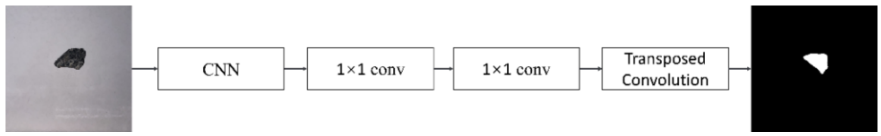

Figure 1. FCN model structure.

PSPNet also uses convolutional neural network to achieve feature extraction, in which ResNet is used as the backbone network, and the obtained feature map is pooled through the pyramid pooling module with four different sizes of 1×1, 2×2, 3×3 and 6×6. For its feature map, the feature map is restored to the size of the feature map through bilinear difference, and the final result is obtained through a convolution layer after connecting with the original feature map. The structure of PSPNet is shown in Figure 2.

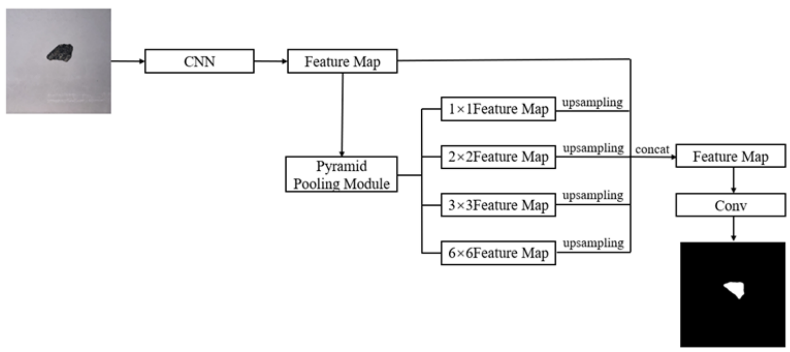

Figure 2. PSPNet model structure.

DeepLabv3+ adopts an encoder-decoder structure, the encoder adopts deep convolutional neural network (DCNN) to achieve feature extraction, and a low-level feature and a high-level feature are obtained. The high-level feature obtains 5 different feature maps through 5 different operations of Atrous Spatial Pyramid Pooling (ASPP), and the 5 feature maps are connected and then the output is obtained by a 1×1 convolution. In the decoder, the low-level feature is added to the output of the encoder with 4x upsampling after a 1×1 convolution, and then a 3×3 convolution is performed, and the segmentation is obtained after 4x upsampling. As a result, the DeepLabv3+ structure is shown in Figure 3.

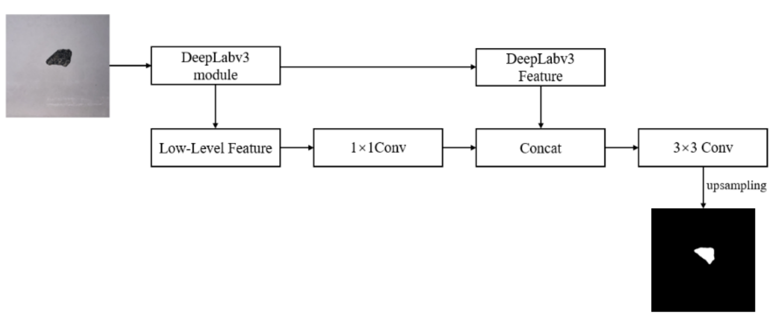

Figure 3. DeepLabv3+ model structure.

DANet uses ResNet to achieve feature extraction, and passes the obtained feature map through two attention modules: position attention module and channel attention module. In the position attention module, self-attention is used to obtain the spatial dependencies of any two positions in the feature map, and the dependencies between channels are obtained in the channel attention module. Finally, the features of the two attention modules are fused and upsampled to obtain the final result. The model structure is shown in Figure 4.

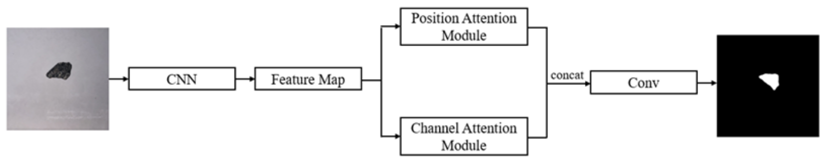

Figure 4. DANet model structure.

Attention-UNet adds an attention mechanism to the traditional UNet structure. The traditional UNet encoder consists of two 3×3 convolutional layers and a 2×2 maximum pooling layer repeatedly, and the decoder consists of a 2×2 upsampling convolutional layer and the decoder layer upsampling results. The result of adding the feature map output by the corresponding encoder and two 3×3 convolutional layers. Attention-UNet adds an attention mechanism where the upsampling result is added to the feature map output by the corresponding encoder, which can effectively suppress activation in irrelevant regions and reduce redundant information. The model structure is shown in Figure 5.

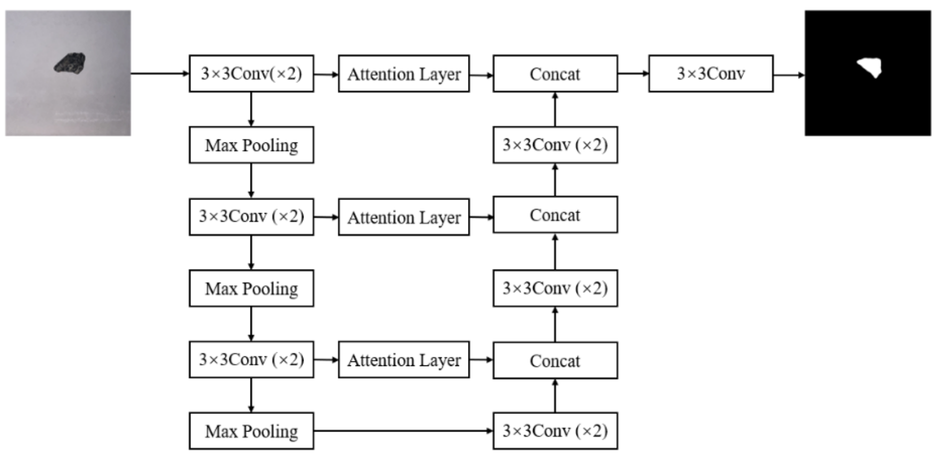

Figure 5. Attention-UNet model structure.

3. EXPERIMENTS

3.1 Dataset

Using the camera to collect the top view of the aggregate, the size of the collected image is 3124×3124 pixels. After comprehensively considering the segmentation time and effect, the image is reduced to 512×512 pixels, and the reduced image was labelled by labelling software "LabelMe". The aggregate sample is shown in Figure 6a. labels are shown in Figure 6b.

(a) Aggregate samples (b) Labels

Figure 6. Aggregate samples and labels.

3.2 Evaluation indicators

Pixel accuracy (PA), Precision (P), Regression (R), Intersection over Union (IoU), and F1 score (F1) are used as evaluation indicators to evaluate the segmentation results. The calculation formula is shown in equations (1)-(5).

$$PA = \frac{TP + TN}{FN + FP + TP + TN} \tag{1}$$

$$P = \frac{TP}{TP + FP} \tag{2}$$

$$R = \frac{TP}{TP + FN} \tag{3}$$

$$IoU = \frac{TP}{TP + FN + FP} \tag{4}$$

$$F1 = 2 \times \frac{P \times R}{P + R} \tag{5}$$

3.3 Results

After using each model for segmentation, the segmentation evaluation of each model is shown in Table 1.

Table 1. Results of each model.

Model	PA	P	R	IoU	F1 score
FCN	0.9986	0.9768	0.9765	0.9543	0.9766
PSPNet	0.9985	0.9778	0.9690	0.9479	0.9732
DeepLabv3+	0.9987	0.9778	0.9806	0.9592	0.9791
DANet	0.9988	0.9809	0.9602	**0.9786**	0.9796
Attention-UNet	**0.9991**	**0.9842**	**0.9852**	0.9698	**0.9846**

After the segmentation is completed, the minimum circumscribed circle diameter is calculated for the segmentation result graph to obtain the aggregate particle size, as shown in Figure 7.

Figure 7. Image segmentation results and particle size calculation.

3.4 Discussion

With the development of deep learning technology, more and more crushing companies have introduced intelligent production lines. In terms of aggregate gradation, traditional detection methods are time-consuming and labor-intensive, and the accuracy is affected by the operator. Therefore, many companies have introduced digital image processing technology to perform the grading of aggregates manually. Using digital image processing technology can greatly reduce costs and improve detection efficiency, but most companies use traditional image segmentation algorithms, such as threshold segmentation, edge detection, etc. Traditional image segmentation algorithms only extract low-level semantic information such as color and texture of image pixels, so there will be a problem of poor segmentation effect in actual use. For segmentation using deep learning, in addition to obtaining low-level semantic information, it can also obtain high-level semantic information such as objects contained in the region. Therefore, semantic segmentation combined with deep learning can often achieve better results and higher accuracy.

The five models used in this study have different technical concepts. FCN is a method based on full convolution, PSPNet is a method based on feature fusion, DeepLabv3+ is a method based on atrous convolution, DANet is a method based on attention mechanism, and Attention- UNet is a method based on encoding and decoding. According to the experimental results, we find that the accuracy of each deep learning method is very high, which caused by the simple aggregate data set used. In the following research, the background obtained by actual shooting will not be single aggregate images for experiments.

4. CONCLUSION

Aiming at solving the problems of high artificial subjectivity and low efficiency in the current industrial aggregate grading method, this paper combines the deep learning method to realize the detection of aggregate digital images, and obtains the aggregate particle size by calculating the minimum circumscribed circle diameter of the aggregate to realize the grading of the aggregate. Experiments show that the method combined with deep learning has high accuracy, fast speed and high efficiency. Among them, Attention-UNet has the highest accuracy rate in the model, which can effectively improve the accuracy of aggregate classification in industrial production, and has a great impact on the sand and gravel aggregate industry. Intelligence is of great significance.

With the continuous growth of artificial intelligence technology, the intelligent development of the sand and gravel aggregate industry has become an increasingly common trend. In future research, the volume of aggregate will be calculated by obtaining the characteristics of more angles of aggregate, and then the quality of aggregate will be calculated to achieve intelligent grading.

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