Intelligent Transportation and Smart Cities
V. Mezhuyev et al. (Eds.)

doi:10.3233/ATDE240395

A Support Vector Regression-Based Method for Stone Powder Detection in Machine-Made Sand

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Abstract. Aiming at the problems of cumbersome steps, low accuracy and difficult to quantify in the detection method of stone powder content of machine-made sand, a quantitative stone powder detection method is proposed. Based on the image segmentation results, the stone powder attached to the sand surface and the scattered stone powder were calculated separately. Then, a support vector regression (SVM) model was used to obtain the mapping relationship between the two and the methylene blue value to quantify the total stone powder content of machine-made sand. The experimental results show that the obtained value of 0.9239 proves that there is a high correlation between the method and the methylene blue value, thus verifying the effectiveness of the method in quantifying stone powder. The stone powder detection method for machine-made sand proposed in this paper further realises the quantitative function of qualitative analysis, provides a new technical method for the quality detection process of machine-made sand, and also has important practical significance in the direction of the construction of the smart city.

Keywords. Road material; Machine-made sand; Detection of the stone powder; Quantification of stone powder; Machine learning.

1. Introduction

The stone powder content in machine-made sand [1] can have a negative impact on the strength, workability, durability, and even economy of concrete. The detection of stone powder in mechanism sand can improve the quality of concrete in smart city construction and achieve automation and intelligence in building material production [2]. Currently, in order to determine the content of stone powder on the surface of machine-made sand, the industry usually uses the methylene blue test (MC test) [3]. However, this method involves several steps such as weighing, mixing, drying and cooling, and is relatively cumbersome to operate [4]. In addition, the accuracy and efficiency of this testing method are often difficult to ensure due to errors in manual observation, environmental factors, and other external interferences. Therefore, it is

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especially urgent and critical to explore and realize the intelligent detection method of stone powder content in machine-made sand.

Most of the current studies on machine-made sand are concentrated on its effect on concrete. In order to make full use of stone powder, a by-product of mechanism sand, Nie et al. [5] found through tests that supplementary adjustment of water consumption in the part of stone powder more than 7.0% can improve the working performance of concrete with little effect on the final strength and durability. For concrete with high early strength requirements, the stone powder content of machine-made sand should be controlled not to be too much. Khan K et al. [6] investigates the compressive strength of concrete made of manufactured sand as a partial replacement of normal sand. The prediction model, i.e., gene expression programming (GEP), was used to estimate the compressive strength of manufactured sand concrete (MSC). The mathematical expression achieved from the GEP model revealed that six parameters, namely the compressive and tensile strength of cement, curing period, water–binder ratio, water–cement ratio, and stone powder content contributed effectively among the 11 input variables. Feng et al. [7] investigated the effect of stone powder content and parent rock type on the properties of machine-made sand concrete. The results showed that increased stone powder content inhibited cement hydration and increased the amount of unhydrated cement and fly ash. The Ca/Si of C-S-H gel was lowest when the concrete compressive strength was optimal.

There are still few studies on the detection of stone powder content in machine-made sand, and the current detection methods are limited to traditional equipment detection and image color conversion. In order to quantify the amount of stone powder in machine-made sand images, the stone powder portion needs to be accurately identified and segmented. Given the advantages of deep neural networks in feature extraction and image segmentation [8], we use deep learning segmentation methods to deal with this problem. Deep learning methods can autonomously learn task-relevant features from images for accurate pixel classification and end-to-end segmentation. Convolutional Neural Networks (CNN) [9] and Fully Convolutional Networks (FCN) [10] are used as key underlying networks to make breakthroughs in graph segmentation, while the attention mechanism [11] also shows high application value in segmentation tasks. Based on the research progress of machine-made sand powder by scholars all over the world, several drawbacks of machine-made sand powder detection still exist. It should be noted that research on the detection of sand and stone powder content mainly includes qualitative analysis of whether the stone powder content is qualified, lacking specific quantitative parameters.

To address the above problems, a quantization method based on the SVM model is proposed. The process of the study is shown in Figure 1. Applying deep learning and image segmentation technology to the research on stone powder detection. Based on the segmentation results, get the stone powder area and calculate the part of the stone powder scattered by the sample. Then, calculate the part of the stone powder attached to the surface of the machine-made sand. Finally, use the support vector machine regression model to complete the quantitative analysis of the batch of stone powder. The method will provide technical support for the construction of smart cities and promote innovative development in the construction industry.

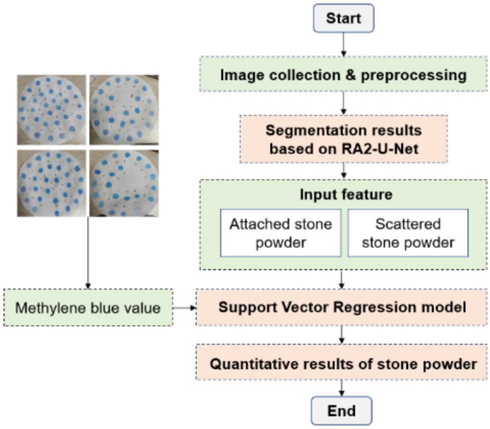


Figure 1. Flowchart of the Quantitative Segmentation of Stone Powder in machine-made sand.

2. Methodology

2.1. Segmentation Method Based on RA2-U-Net Modeling

Due to the inconspicuous features of the pixels adhering to the stone powder in the 2D machine-made sand image and the low contrast, this study took the surface without stone powder as the segmentation target (the exposed area of the machine-made sand). Subsequently, the overall machine-made sand pixel area and the segmentation result were used to calculate the difference, and finally obtain accurate machine-made sand that adheres to the stone powder pixels. In this study, the RA2-U-Net network [12] was used to segment the results of exposed areas of machine-made sand, which were then further quantified based on the results.

The preprocessed machine-made sand images were divided into a training set and test set according to the ratio of 8:2. The Adam optimizer was used to update the parameters, and the callback function ModelCheckpoint in Keras was employed to save the optimal model. The Bath_size of both training and testing was 2, with a total of 150 rounds of training. The accuracy rates of the training set and validation set of the RA2-U-Net network tend to become stable at 0.9291 and 0.9395, respectively; the loss values in the training set and validation set tend to become stable at 0.1678 and 0.1682, respectively.

2.2. Methylene Blue Detection Method for Stone Powder

The JTG E42-2005 "Highway Engineering Aggregate Test Regulations" standard specifies the detection method of machine-made sand and stone powder, that is, the methylene blue test. In this setting, the principle is that the powder, carried and scattered by the machine-made sand particles, presents a certain adsorption capacity for the methylene blue reagent. Hence, when the methylene blue reagent consumes all the powder, it becomes in a free state. Reflected on the color halo chart is a radial light blue halo, which means that the amount of machine-made sand powder is determined by the amount of methylene blue reagent that is used. Afterwards, the methylene blue value MBV is calculated as follows:

$$MBV = \frac{V}{m \times 10} \tag{1}$$

Where MBV represents the grams of methylene blue consumed per kilogram of the sample (g/kg); m is the mass of the sample (g); V denotes the consumption of methylene blue reagent (mL); the coefficient 10 is used to reflect the sub-Nail blue quality.

2.3. Support Vector Machine Regression Model Construction

In using the support vector machine (SVM) [13,14] to analyze the mapping relationship between the attached stone powder and scattered stone powder of machine-made sand and the methylene blue value, we can construct a support vector regression (SVR) model, especially choosing the polynomial kernel function (poly kernel function). The basic form of the SVR model can be expressed as:

$$f(x) = \sum_{i=1}^{N} \alpha_i \cdot K(x_i, x) + b \tag{2}$$

Where f(x) is the predicted dependent variable, $\boldsymbol{\alpha_i}$ is the coefficient of the support vector, $\mathbf{K(x_i, x)}$ is the kernel function, and b is the bias term.
For polynomial kernel function basic form can be expressed as:

$$K(x, y) = (x \cdot y + c)^d \tag{3}$$

Where c is a constant and d is the number of polynomials. This kernel function allows the model to capture the complex relationships of the data in a nonlinear space.

The model is characterized by attached stone powder F content (%) and scattered stone powder G content (g) as inputs and the value of predicted stone powder content as output.

3. Experiment

The quantification of machine-made sand and stone powder was mainly divided into two parts. One was the quantification of the stone powder attached to the surface of the machine-made sand, which was mainly obtained by the quantitative analysis of the stone powder predicted by the RA2-U-Net model. The other part was the quantification of scattered stone powder, which was the mass (g) of stone powder inferior to 0.075 mm, acquired by standard sieve screening. Since the traditional detection method of machine-made sand was the methylene blue method, the MBV (Methylene Blue Value) was obtained by drying, stirring, and color halo test. Therefore, through the support vector machine regression model, the mapping relationship between the proposed quantization method and MBV was obtained, which proved the effectiveness of the suggested method. The quantification process of stone powder content in machine-made sand is shown in Figure 2:

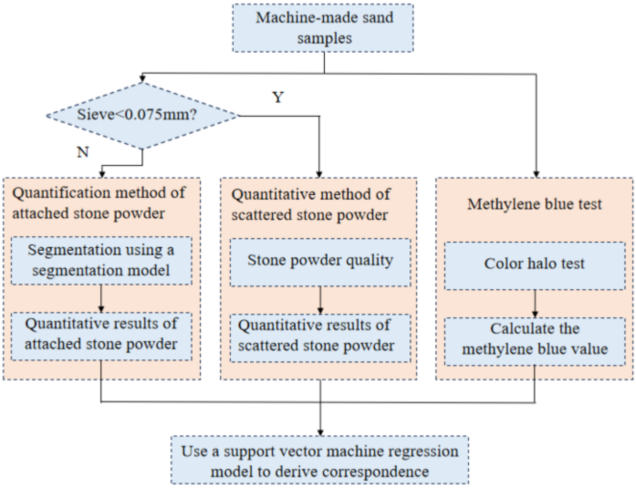


Figure 2. Quantification process of stone powder content in machine-made sand

3.1. The Results of Methylene Blue Test

The methylene blue test was carried out, and a total of 25 samples were prepared from three batches of machine-made sand. The resulting partial color halo image is shown in Figure 3, while Table 1 shows the methylene blue value obtained for each sample.

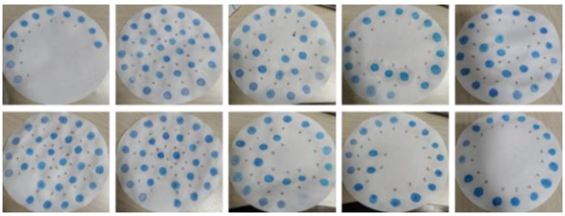


Figure 3. Example of methylene blue test color halo

Table 1. MBV of different samples

Machine-made sand batch 1		Machine-made sand batch 2		Machine-made sand batch 3	
Sample number	MBV/(g/kg)	Sample number	MBV/(g/kg)	Sample number	MBV/(g/kg)
1	0.85	12	0.825	19	1
2	0.9	13	0.9	20	1.2
3	0.95	14	0.975	21	1.3
4	1	15	1	22	1.375
5	1.05	16	1.05	23	1.4
6	1.15	17	1.1	24	1.5
7	1.225	18	1.15	25	1.55
8	1.3	/	/	/	/
9	1.35	/	/	/	/
10	1.45	/	/	/	/
11	1.5	/	/	/	/

3.2. Quantification Method of Attached Stone Powder

The area of the machine-made sand distribution area was calculated by counting the number of pixels. Afterwards, the ratio of the stone powder area was obtained by making a difference, that is the stone powder content. The number of pixels in the machine-made sand area was recorded as $\boldsymbol{a_1}$, and the pixel distribution is shown in Figure 4(b). The total area of machine-made sand particles was calculated using the method of connecting the center of the pixel points, where the total number of pixels was recorded as $\boldsymbol{b_1}$; the pixel distribution is shown in Figure 4(c). At this time, the ratio of the area of the machine-made sand area in the image to the total area of the machine-made sand particles was $\frac{\boldsymbol{a_1}}{\boldsymbol{b_1}}$, which represents the area content of the machine-made sand in the original image (Figure 4(a)). F denotes the stone powder content of the whole batch of machine-made sand, which is the proportion of all stone powder to all machine-made sand particles, and the calculation is shown in (4):

$$F = 1 - \frac{a_1+a_2+a_3+\cdots+a_n}{b_1+b_2+b_3+\cdots+b_n} \tag{4}$$

Where $\boldsymbol{n}$ represents the number of machine-made sand images in this batch, $\boldsymbol{a_n}$ the number of pixels in the machine-made sand area in the nth machine-made sand image, and $\boldsymbol{b_n}$ the total number of pixels of machine-made sand particles in the nth machine-made sand image.

(a) Original image (b) Area of machine-made sand area (white) (c) Total area of machine-made sand (white)

Figure 4. Area calculation of machine-made sand

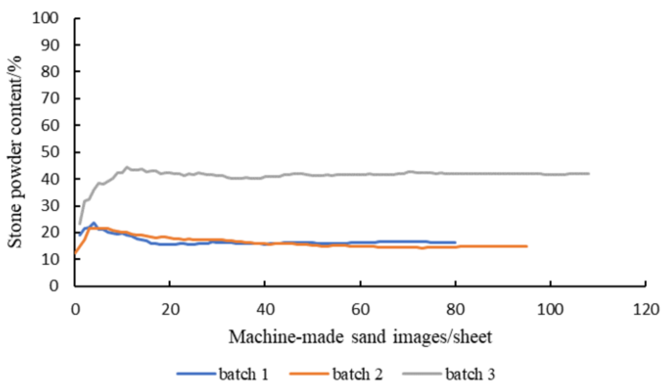


Figure 5. Quantitative results of the content of machine-made sand and stone powder

3.3. Quantitative Method of Scattered Stone Powder

A total of three batches of machine-made images, 20, 23, and 27 images, were collected, and each image was divided into four equal parts, which were expanded to 80, 92, and 108 images, respectively. Afterwards, these images were segmented and the stone powder content was quantified; the results are shown in Figure 5. It can be clearly seen that the curves of the stone powder gradually tend to the stable values of 16.36%, 14.81%, and 41.96%, respectively. Compared with the corresponding methylene blue values of 0.85, 0.825, and 1 g/kg, it can be deduced that the strong correlation verifies the feasibility of the proposed method for the quantification of attached stone powder.

Since scattered stone powder was present in the sample, the content of this part of the stone powder should be quantified. The scattered stone powder was obtained by sifting through a standard sieve of 0.075 mm, and then weighing it using an electronic scale (weighing 400 g, with a sense of 0.01 g) with a 0.01 g accuracy, and recording its mass G. The first batch of machine-made sand was prepared by adding 0g, 1.5 g, 3 g, 4.5 g, 6 g, 7.5 g, 9 g, 10.5 g, 12 g, 13.5 g, and 15 g of scattered stone powder to each 200 g of machine-made sand particles to prepare samples 1 to 11. In the second batch of machine-made sand, 0 g, 1.5 g, 3 g, 4.5 g, 6 g, 7.5 g, and 9 g were added to every 200 g of machine-made sand particles to prepare samples 12 to 18. In the third batch of machine-made sand, 0 g, 1.5 g, 3 g, 4.5 g, 6 g, 7.5 g, and 9 g were added to every 200 g of machine-made sand particles to prepare samples 19 to 25.

4. Results and Discussion

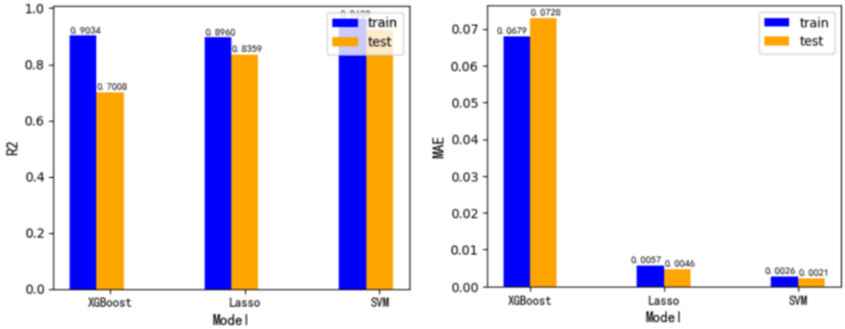
The quantification of machine-made sand and stone powder was mainly divided into two parts. One was the quantification of the stone powder attached to the surface of the machine-made sand, which was mainly obtained by the quantitative analysis of the stone powder predicted. Second, after obtaining the quantitative values of the attached and scattered stone powders in the machine-made sand, it was necessary to form a mapping relationship with the corresponding MBV. In this case, the SVM model utilizes a polynomial kernel function to quantitatively explain a certain nonlinear relationship between the dependent variable and multiple independent variables. In this study, the content of attached stone powder F (%) and the content of scattered stone powder G (g) were employed as independent variables, and the methylene blue value MBV (g/kg) was used as the dependent variable.

The model evaluation index employed the significant value $\boldsymbol{R^2}$ which was used to reflect the proportion of all the variations of the dependent variable that could be explained by the independent variable through the regression relationship. The calculation formula is as follows:

$$R^2 = \frac{\sum(\hat{y}_i-\bar{y})^2}{\sum(y_i-\bar{y})^2} \tag{5}$$

Where $\boldsymbol{y_i}$ is the ith data value of the dependent variable, $\boldsymbol{\hat{y}_i}$ is the predicted value of the regression equation for the ith observation, and $\boldsymbol{\bar{y}}$ is the mean of the dependent variable.

There are 25 sets of data in the dataset, of which 20 sets are used as training sets and 5 sets are used as test sets. The BPNN, XGBoost [15] and Lasso [16] algorithms are selected for comparison with SVM. It is found that the BPNN model is less efficient because BPNN usually requires a large amount of data for training to capture the complex patterns in the data. The prediction accuracies of XGBoost, Lasso regression, and SVM are all greater than 0.7. The comparison of the accuracies and errors of the three models are shown in Figure 6, respectively.



(a) Comparison of prediction accuracy of different models

(b) Comparison of prediction error of different models

Figure 6. Comparison of different models in stone powder quantification

From the Figure 6, it can be seen that the training accuracy of XGBoost model is high, the $\boldsymbol{R^2}$ is 0.9034 , but the accuracy of this model on the test set is low, the $\boldsymbol{R^2}$ is only 0.7008. XGBoost may have over-fitted the noise or local features in the training data, which leads to the poor performance on the new data. The values of the training set and the test set of Lasso regression are 0.8960 and 0.8359, respectively. The overall prediction accuracy is not particularly high, which may be because Lasso regression tends to favor one independent variable and ignore the influence of other independent variables when there are multiple independent variables. On small datasets, the model may not be able to fully learn the underlying structure in the data due to the limited number of samples, resulting in a limited selection of features. The SVM model uses a polynomial kernel function, which is suitable for dealing with nonlinear relationships, and performs well with small sample sizes. In the training process, the parameter of kernel function C is set to 0.1, coef0 is set to 2, degree is set to 2, and gamma is set to 0.1. The results show that the SVM model has high training and prediction accuracies, and the $\boldsymbol{R^2}$ is 0.9609 and 0.9239, respectively.

The specific parameters of the 5 sets of test data are shown in Table 2. It is clear that the absolute errors of the actual value and predicted value of the 5 sets of test data are significantly low, and the $\boldsymbol{R^2}$ reaches 0.9239 which indicates that the proposed quantitative method for the content of machine-made sand and stone powder fits well the quantification method specified in the national test specification.

Table 2. Comparison of true value and predicted value

Sample	Independent variable	True value	Predicted value	Absolute error
1	(16.36,1.5)	0.9	0.9667	0.0667
2	(16.36,4.5)	1	1.0474	0.0474
3	(14.81,7.5)	1.1	1.1175	0.0175
4	(39.21,6)	1.35	1.4065	0.0565
5	(41.96,6)	1.4	1.4515	0.0515

The significant value R^2=0.9239 was obtained by calculation, indicating that the closeness of the correlation between the variables is strongly correlated. Furthermore, this confirms that the suggested method for quantification of stone powder forms a satisfactory mapping relationship with the methylene blue value and further proves the reliability of the method for evaluating the content of machine-made sand and stone powder.

5. Conclusion

This paper proposes a detection method that can quantify stone powder based on segmented images. The main conclusions can be summarized as follows:

The adhering stone powder and the scattered stone powder on the sand-making surface were calculated. The support vector regression model was used to derive a mapping relationship between the two and the methylene blue value to quantify the total stone powder content of the machine-made sand. The $\boldsymbol{R^2}$ value obtained from the experiment was 0.9239, which shows the high correlation that exists between the variables. The study is crucial for smart city construction by accurately quantifying the content of machine-made sand and stone powder to achieve smarter and more efficient material utilisation in the construction sector.

Due to the limited shooting range of the microscope, the stone powder detection method in this study is only applicable to the machine-made sand particles within the shooting range of the microscope. Moreover, the future work can increase the characteristics of machine-made sand by expanding the sample size, thereby improving practical applicability.

Aknowledgement

This work was supported by Gansu Provincial Department of Transportation Science and Technology Project (2022-03)

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