Scholar Publishing Group
International Journal of Engineering Technology and Construction
https://doi.org/10.38007/IJETC.2020.010305
ISSN 2789-7176 Vol. 1, Issue 3: 54-63

Common Cracks of Mass Concrete in Construction Quality by AFM

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Keywords: Atomic Force Microscope, Concrete Structure Health Monitoring, Monte Carlo Sampling, Bayesian Inference

Abstract: It is very important to observe the health monitoring (SHM) of mass concrete structure by atomic force microscope (AFM) for the safety and sustainability of the structure. SHM model is proposed, in which Monte Carlo sampling can be used to quantify the uncertainty. Using Bayesian inference, three independent case studies are studied: crack, local damage identification and building main component detection. In addition to uncertainty indicators show that the mean softmax variance and entropy have a good correlation with miss classification. Although uncertainty indicators can be used to trigger which can further improve performance. The results show that this method is superior to the latest one. In the actual scene test, the crack segmentation accuracy is 91%, and IOU is 78%. The accuracy of damage segmentation is 83% and IOU is 73%, which shows that this study can be fully used in the actual production process. It can be seen from these that the method proposed.

1. Introduction

Building body inspection is an essential assessment. In recent years, with the growth of people's economy, the mainstream of structure form has also changed from brick-concrete structure form to cast-in-place reinforced concrete brown form, which has greatly improved the environmental appearance of alkali town and improved people's living standards. At the same time of the rapid development of the construction industry, complaints about the construction quality are also rising trend, among which the crack problem has become the focus of the current complaints. These cracks not only bring inconvenience to users, but also affect the enterprise reputation image of the development unit and the construction unit, and cause economic waste in maintenance. All parties in social affairs are looking for ways to control cracks in the design and construction process, and strive to do a good job in the crack control project.

At present, surface analysis and recover lost sensor data. SHM uses risk, which is a significant benefit of this research. The input information of this model can come from various sources, such as vibration, acoustic emission and strain measurement. Although structural damage can be well indicated, special instruments are usually required to obtain these types of records [1-2].Many concrete structures have cracks of different degrees and different forms in the process of construction and use. The cracks of reinforced concrete structures are a common technical problem. The destruction and collapse of the structure begin from the expansion of cracks, such as strong earthquake after the earthquake area of the building is full of various cracks, a large number of cracks on the reinforced concrete beam load test and so on. So people often produce a kind of precursory fear of destruction to crack. Indeed, the expansion of cracks is the initial stage of structural damage, structural cracks can cause leakage, resulting in the reduction of lasting strength, such as protective layer peeling, steel corrosion, concrete carbonation and so on. Therefore, the concept of custom, even some acceptance codes and some engineering sites do not allow cracks in structures.

Bao identified structural components by predicting the bounding box of the object (and the pixel level segmentation of the entire scene). The advantage of this method is that it can effectively identify each component and then conduct detailed analysis, but it requires a large number of labeled data sets, as well as a long and harsh environment [3]. Chen used different algorithms to study the pavement defects and road conditions, including probability generation model and support vector machine, convolution neural network and recurrent neural network, and uses the boundary box or semantic segmentation to identify the SHM of cracks. This way can effectively avoid the dependence on data, but it also poses a great challenge to the construction of algorithm [4]. Zhang used the deep learning framework to study, such as delamination, cavity, fatigue crack and weathering, or uses the deep learning framework to identify some of them. The same way has the advantages of simple and efficient, and the performance can achieve an excellent purpose, but the same disadvantage is obviously that the data dependence is too high, and The generalization ability of the model is not enough [5].Model as feature extraction and training, inference will use Bayesian model.

Model is very high (for example, monitoring the damage of large buildings), the uncertainty output and prediction of the model. Model according to several performance indicators. Although the Bayesian model has excellent robustness, we propose a novel alternative method.The distribution of these micro-cracks in concrete is irregular and non-penetrating along the section, so within the limit of deformation still has good compressive and shear properties, and can withstand a certain tension. When the structure is subjected to external force, temperature, the stress action caused by internal chemical reaction exceeds a certain level, these cracks will gradually connect through, development and expansion, thus developing into macro cracks.

2. Deep Learning Framework with Bayesian Inference

Uncertainty should be a natural part of the output of any prediction system, and we can trust that it is crucial for decision-making to undermine the confidence of diagnostic output. Bayesian probability theory provides a mathematical framework to infer model uncertainty, but it usually brings high computing a well-known probability model: Bayesian approximation with Gaussian process has a priori probability, which sets a part of the input elements at random to zero to reduce over fitting when training neural networks [6]. Standard probability uses the weighted average technology in the test [7].

The training network, i.e. the objective function by applying Bernoulli distribution on the network weight, the missing value the model. This can be achieved by using randomly discarded cells to sample the network [8].Coagulation soil, as the largest and most widely used construction material, has been widely used in water conservancy, industrial and civil architecture, agriculture and forestry, urban construction, harbor and transportation engineering, and cast-in-place concrete floor slab in residential engineering is a very important structural component of construction engineering. As mentioned above, concrete is prone to crack is its biggest disadvantage. Harmful cracks on the concrete floor will not only reduce the strength of concrete, and even lead to the occurrence of some engineering quality accidents, especially, it will reduce the ability of concrete to resist external material erosion, greatly reduce the durability and service life of concrete floor. This paper probes into the causes of common cracks in reinforced concrete cast-in-place floor slab in residential engineering and its control measures.

Output (y) is the shape tensor (height, width, number of channels), and the last channel refers to the category, activating the dropout level in reasoning will produce prediction output, in which the category probability can be regarded as a random variable[9].

$$p(y=i \mid X,Y) \approx E(S_i) = \frac{1}{N}\sum_{n=1}^{N_s} S_i^n \tag{1}$$

$$H(p) = \sum_{i=1}^{N_b} - P_i \log(P_i) \tag{2}$$

Concrete pouring initial stage is heating stage, in the plastic state, the elastic modulus of concrete is very small, the temperature stress caused by the deformation change is also very small, generally can be ignored. However, after several days, the elastic modulus of concrete rises rapidly with time, and the temperature stress caused by deformation changes also increases significantly with the increase of elastic modulus. Therefore, the change law of elastic modulus must be considered.In addition, the category category. Equation (3) obtains this indicator by obtaining the sample variance of the Monte Carlo sample Si for each category:

$$CSV_i = \frac{1}{N_s - 1}\sum_{n=1}^{Ns}[S_i^n - E(S_i)]^2 \tag{3}$$

For example, prediction tags with high softmax probability may have high model uncertainty [10].In practice, concrete blocks are not insulated. After concrete is poured, there is an initial temperature (i.e. pouring temperature). Subsequently, on the one hand by the influence of cement hydration heat, concrete internal temperature will rise gradually, the other - respect as a result of heat exchange with the surrounding medium, heat is constantly sent out. Therefore, the actual temperature inside the concrete in the non-adiabatic state is a process of change from low to high and from high to low. The temperature tends to be stable until the influence of various initial factors (hydration heat, pouring temperature, etc.) gradually disappears.

2.1. Convolution Neural Network

Because of its excellent function, researchers use CNN function for building.By classifying each pixel, this method is applied to crack segmentation. In order to find the defect degree in the large image, a simple method is to use a fixed size sliding window to scan the image and mark the window detected by the classifier. According to this method, the results show that CNN can achieve high accuracy in damage classification [11].

(1) Two stage detection

Common cracks in concrete structure construction process although there are dozens of types, but its characteristic and forming regularity of each are not identical, in practical engineering, the causes of the formation of cracks often is caused by many factors, the actual construction process of concrete appear crack, mostly due to shrinkage, shrinkage, temperature stress, the early plastic shrinkage and spontaneous contraction contraction caused by superposition. There are main factors among them, also have secondary factors, because this distinguishes primary and secondary factors, to concrete structure crack reason gives scientific correct "diagnosis", to prevent concrete structure crack just is crucial, ability suit the remedy to the case, reduce or avoid harmful crack happening.Faster R-CNN uses shared computing and neural networks to suggest regions, which improves the speed and accuracy of its previous products.

(2) Single stage detection

SSD and Yolo both delete the proposed region generation step. This shows that there are a lot of localization errors. In order to make up for these shortcomings, some improvements are introduced to enhance the performance of the network, including the application of batch normalization and the use of good prior. In recent publications, solid-state drives are used to detect building damage in real time. They have proved that SSDs can achieve relatively high accuracy for some types of defects [12].

2.2. Transfer Learning

Then the weights of pre-training interesting tasks. The results show that, compared with the frozen transfer feature layer, the transfer feature and then fine tune it can provide better results. In addition, better performance can be achieved by transferring more feature layers. In order to use TL for yolv3, the trunk of yolv3 is initialized on the Imagenet dataset with the pre-trained weight of darknet-53.

3. Experimental Models and Data Sets

3.1. Model Building

This architecture has achieved the most advanced performance in the benchmark data set for urban scene segmentation, and is considered to be one of the most successful architectures for specific tasks. The entered spatial resolution is then restored in the upper sampling path. There is a bottleneck between the two paths. The details of each unit are shown in Figure 1.

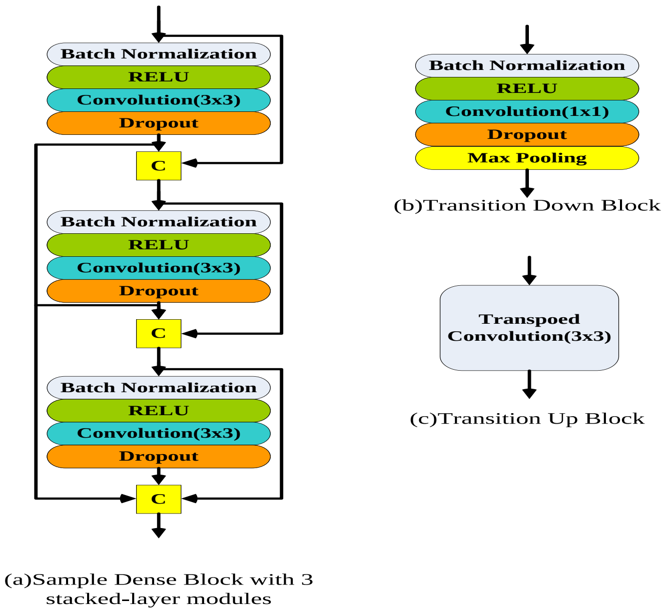

Figure 1. FC-DenseNet building blocks

As can be seen from Figure 1, dense blocks are composed of layers, customized to improve the computing efficiency.

3.2. Experimental Setup

Using the keras API, the three models were trained a batch size of 2, each with 8 GB of memory. The observation results were randomly grouped, and 70% of the data was used for training, the rest was used as test set. In addition, 30% of the training observation results were used as verification set, and the (each period) can achieve faster convergence with fewer periods. L2 regularization is also used to improve numerical stability and reduce over fitting. According to the verification loss, all models are trained for up to 200 cycles, and 15 cycles are stopped in advance. In the training, 1.0e-4 learning rate and 0.9996 exponential decay rate are also used.

3.3. Binary Crack Detection

The binary research fields of automatic SHM.The cracked forest data set is used. The data set includes 118 atomic microscope. The image is with an atomic microscope at almost constant photographic settings about the state of the building, and the correct result.

Which uses the maximum value of softmax probability. Researchers have proposed intermediate frequency weighting (MFW) allocation to help improve the accuracy of average classification (MCA). In recent work, researchers have weight of crack and background pixels are equal, the loss function will be minimized, and ml decision rules are used to assign labels to each pixel.

3.4. Damage Location Detection

This research also focuses on the existence of location damage. In recent years, on the one hand, through the study of concrete strength beyond the micro, on the other hand, but also through a lot of engineering practice experience, researchers found that for concrete structure, cracks cannot be completely avoided for certain, this and the characteristics of the material itself is inseparable. If we in the structural design and construction of the building concrete component anti-cracking requirements are too high, from the point of view of engineering economy is not economic; How to control the harmful degree of cracks in concrete within the allowable range is the focus of current research. It is of great significance to study how to control the cracks of reinforced concrete floor slab reasonably according to the existing national conditions and national strength. However, due to the various reasons for building cracking, the problem is more complex, often cannot be used to explain the phenomenon of concrete cracks encountered in the actual engineering with the cause of load.

4. Experimental Results and Analysis

4.1. Experimental Analysis of Binary Crack Detection

Table 1 shows the results of six combinations. For the test data set, GA and MCA are obtained. These indexes have little dependence on the data set.

Table 1. Testing performance of 6 different combinations for the Crack Forest dataset

Model ID	GA			MCA			Crack F1 score		
	UW-MAP	UW-ML	MFW-MAP	UW-MAP	UW-ML	MFW-MAP	UW-MAP	UW-ML	MFW-MAP
Benchmark	98.57	98.28	95	77.38	88.93	89.82	60.03	65.81	43.95
Bayesia models	98.77	98.60	97.10	81.51	94.21	94.27	67.21	72.23	53.18
	Crack IOU			Crack precision			Crack recall		
	UW-MAP	UW-ML	MFW-MAP	UW-MAP	UW-ML	MFW-MAP	UW-MAP	UW-ML	MFW-MAP
Benchmark	42.76	48.51	27.62	66.76	55.21	30.43	52.16	81.49	83.29
Bayesia models	51.47	55.87	35.95	70.77	60.18	38.67	64.78	88.29	90.15

As can be seen from Table 1, it is also interesting to choose one model for the three strategies used. Although the overall accuracy of the three crack modes is the highest, several crack modes are missed. On the contrary, in which the accuracy or recall rate of the model is not satisfactory. Since both indicators represent the quality that decision makers must have, Bayesian UW-ML is considered to be the best among other indicators, which accuracy rate, be achieved through count to prove.

4.2. Experimental Analysis of Damage Location Detection

For laboratory experiments, the complexity of this experiment is magnified. In laboratory experiments, UW-MAP strategy is used. Data set is also marked with two categories of binary masks: corruption. The performance indicators of this task are shown in Table 2.

Table 2. Testing performance in bridge component detection

	Background		Damage		Mean value	
	Benchmark	Bayesian models	Benchmark	Bayesian models	Benchmark	Bayesian models
F1-score(%)	92.36	94.04	64.62	71.04	78.26	82.13
Precision(%)	93.17	93.71	64.14	72.21	79.12	83.78
Class Accuracy(%)	92.25	95.61	67.78	68.34	80.05	82.34
IOU(%)	86.61	89.49	47.81	54.01	68.28	72.54

As can be seen from Table 2, compared with the corresponding benchmark, the two models are the same in terms of architecture and training super parameters, with the difference that there is a loss layer in training and reasoning. For all the indexes considered, obvious improvement can be observed, and the segmentation results are highly consistent with the real situation of most of the observed results (including the images obtained from laboratory experiments), but there are some examples showing poor prediction, most of the damaged areas are lost in the test mask. By comparing the basic facts with the uncertainty index, we can see that the damage area of misclassification is related to the higher model uncertainty. This example illustrates the importance of model uncertainty output, which can be used to trigger human intervention. In this case, inspectors can be warned to reassess the condition of the structure.

4.3. Analysis of Cross Validation Results of Transfer Learning

TL-B: initialize the backbone using the pre-trained darknet-53 weights. First, for the first 30 periods, fine tune all layers. Which is about nine times of the building damage data set. In addition, in order to apply the batch re normalization (BR) to the Bayesian models, the super parameters Rmax = 1.5. The cross validation results of transfer learning are shown in Figure 2.

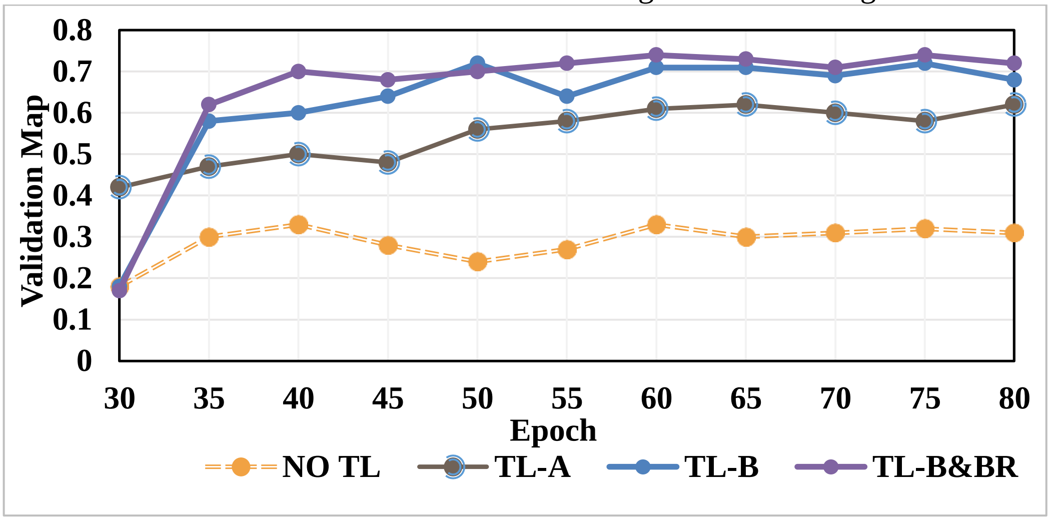

Figure 2. Average validation accuracy at IOU=0.5

It can be seen from Figure 2 that in the last 50 training periods, the verification accuracy when IOU = 0.5. The accuracy of the validation was evaluated. Through the experimental results of different loss functions TL, it shows that the value. The experimental results are shown in Figure 3.

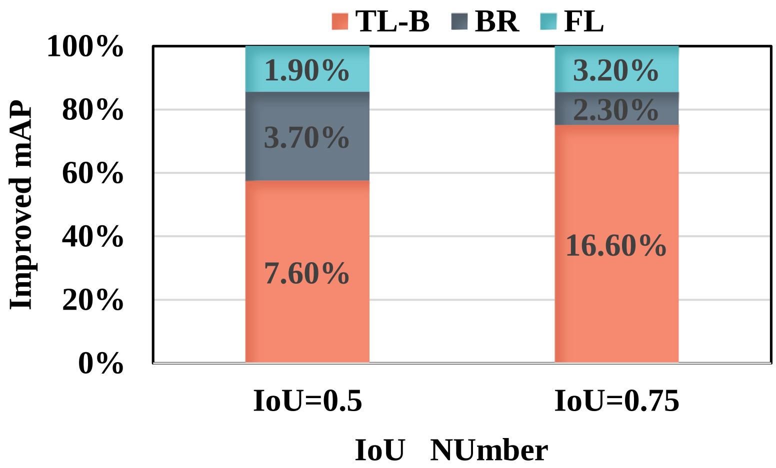

Figure 3. Improvement of validation accuracy

The results from Figure 3 show that TL-B, which uses full pre-training weights from relatively large and similar size datasets, provides the highest accuracy of about map50 = 71.4%, 16.6% higher than TL-A. This shows that using TL-B can achieve more accurate position prediction. Similarly, it is clear that networks map75 is 3.7% and 2.3% respectively. The significant increase causing greater loss of localization.

4.4. Analysis of Transfer Learning Test Results

Unlike super parameters of the model, which is only used to evaluate the performance of the fully specified detector (i.e., generalization). In order to obtain the test results of Bayesian models, all training data are used to train the model again, and the accuracy of the model is evaluated according to the test data. The test results are evaluated according to the different input sizes in multi-scale training.Under different test image sizes, the test accuracy and average accuracy of each category with IOU = 0.5 are shown in Figure 4 and Figure 5.

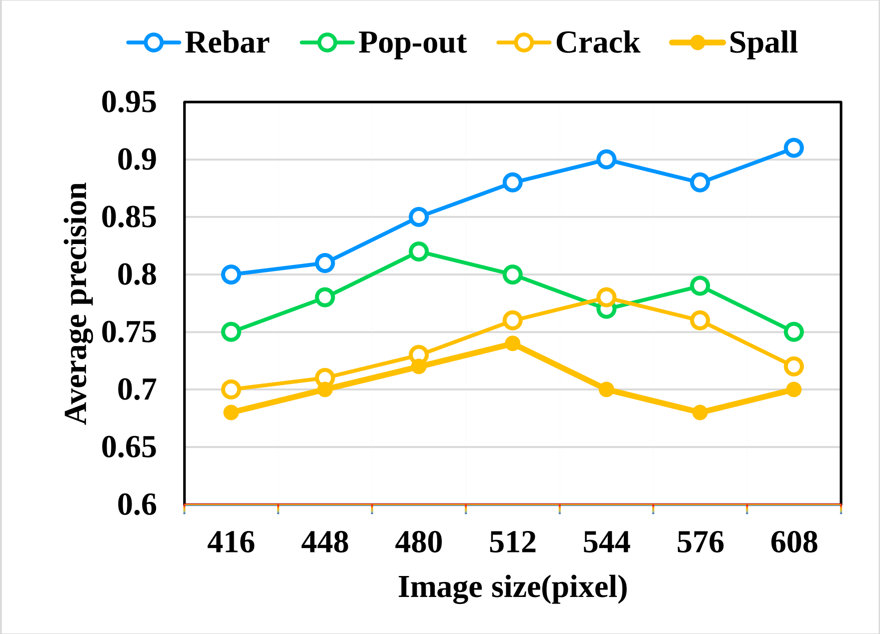

Figure 4. Improvement of validation accuracy

It can be seen from Figure 4 that for the improved Bayesian models, when the input image size is 512, the map50 of crack, pop-up, peeling and exposed reinforcement are 76.5%, model when the input image size is 512. TL method and improved function can provide accurate location prediction in such a small data set. Comparing the average accuracy between different categories, the accuracy of exposed reinforcement is higher than that of the categories.

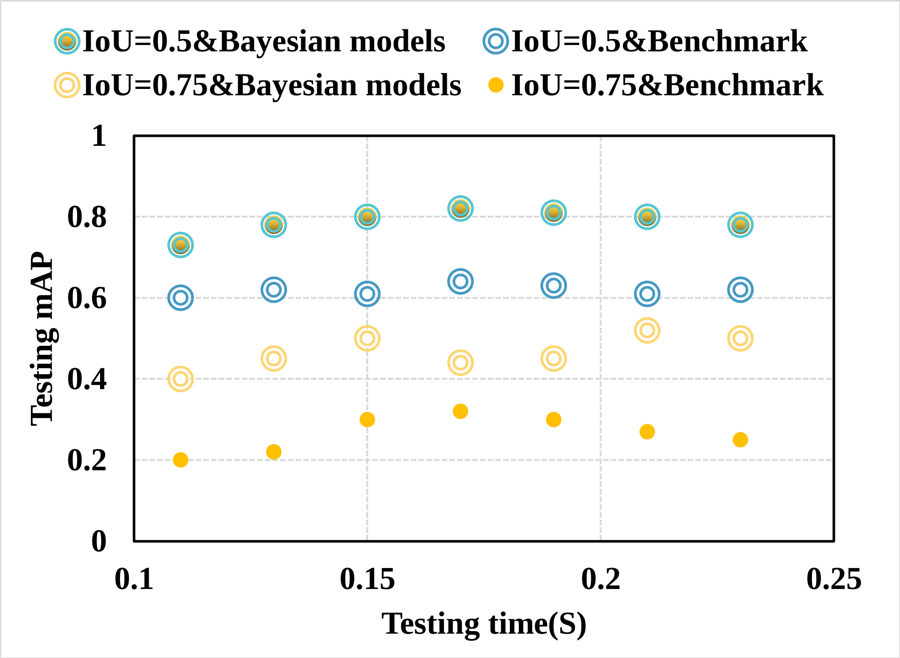

Figure 5. Detection results on testing dataset

According to Figure 5, the average accuracy usually increases with the increase of image size the network to predict well, but receiving field (responsible for detecting large objects) on the lowest resolution feature map is not enough to predict very large objects according to the increased image size.

5. Conclusion

With the deepening of the research and the need of practical engineering, the plastic theory is introduced in the analysis of concrete cracks at present, which fully considers the elastic-plastic properties of concrete and reinforced concrete, and puts forward the strength theory under the limit state, including the limit strength, the limit crack development and the limit deformation of three limit states. These theories are still in use today and continue to evolve. The phenomenological theory has been applied to the study of the strength of building materials under external loads, and the solutions to some practical engineering problems have been given, and certain effects have been achieved. However, the phenomenological theory does not consider the internal structure of concrete, such as the interaction between three phases in concrete and the internal discontinuity of concrete, so the results calculated by phenomenological theory are still quite different from the actual engineering.The latest development of visual inspection. Quantitative model confidence framework. When the reliability of the prediction is in doubt,on visual structure checking, and prove its superiority .

Concrete crack is one of the most common technical problems in construction engineering. Although engineering designers are based on the ultimate bearing capacity of the strength of its structural design, but in practical engineering, cracks are still as a relatively common control standard. For general industrial and civil buildings, small scale of coagulation: soil cracks are generally not dangerous. Only when the crack width reaches a certain extent will it affect the normal use of buildings. If the crack control standard is too strict, it will certainly cause huge economic losses and bring a series of problems. For example, in the earthquake fortification area, if the use of large structural reinforcement rate to control the emergence of building cracks will reduce the ductility of building structural components, reduce the energy dissipation capacity of the structure, the increase of component size will also lead to the increase of building weight, thus increasing the earthquake force.In addition to stronger robustness, Bayesian vision model also provides uncertainty measurement for decision makers. The results show that correlation error classification.

Harmful cracks in buildings are a common technical problem in engineering field, especially the cracks in cast-in-place concrete floor slab in residential engineering. As mentioned above, the factor that causes concrete floor to appear crack is very much, the influence of different type crack to building also is concerned with a lot of factors, be like regional characteristic, use requirement, artificial sensory requirement, environmental change. The development trend of concrete crack and the degree of building harm are also different, so there is a diversified situation of control and treatment scheme.When the confidence level of the model is low, the quantitative measurement of uncertainty. This kind of intervention may. In order to integrate into the automation, an alternative uncertainty auxiliary performance of the model. Check and monitor the existing visual model. In the absence of large training data set. Although we use alternative model, we can customize alternative model.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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