Damage Image Generation of Bridge Column with Conditional Generative Adversarial Network

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SUMMARY

Earthquake disasters will not only cause surface ruptures, landslides, tsunamis, but also lead to accidents such as building and bridge collapses. In addition to providing structural strength to the bridge in the design stage. The damage of the bridge also needs to be assessed after a major earthquake, the engineer should establish a complete evaluation process to facilitate the post-earthquake retrofit of the bridge and ensure the safety of passersby. In order to assist engineers to rapidly evaluate the damage severity of bridge columns, a conditional generative adversarial network(CGAN) model is proposed to generate damage images of bridge columns corresponding to different damage index. The damage image generation model could save the labor and time cost of bridge column damage determination by replacing the complicated manual calculations with artificial intelligence and establish a quick reference for earthquake damage assessment. The result of this study provided an objective and standard evaluation system to assist engineers with seismic damage determination and repair works.

Keywords: bridge scour; stability evaluation; fluid-solid interaction; soil spring.

INTRODUCTION

Earthquake is a major threat to bridge structures. It would not only cause ground cracking, stratum subsidence, tsunamis and other disasters, but also cause collapse on bridge. Therefore, judging the damage degree of the bridge is a key issue to ensure the safety of life and property of passers-by Ogawa et al. published a classification table of RC bridge pier damage after the Hanshin Earthquake in Japan [7]. The shear damage is classified into four types of damage, and then pictures are provided for reference according to the damage degree. On the other hand, an evaluation table for the damage degree of the RC bridge pier base was proposed by the Japan Road Association [8], which compared the residual deformation of the bridge column with large, moderate and small damages under different conditions. The capacity spectrum method proposed by ATC-40 [1] and the displacement coefficient method proposed by FEMA-273 [2] are well-known simplified evaluation methods for bridge damage evaluation. The inelastic response spectrum [3,4] was proposed to replace the high damping elastic demand spectrum to improve the capacity seismic spectrum method. A smooth hysteresis model [5] was proposed by Wang et al. in 2017, which could accurately simulate the hysteresis decay behavior of reinforced concrete bridge columns and the unique loading and unloading paths of reinforced concrete members. The attenuation of the bridge column strength was further combined with the damage index proposed by Park and Ang [6] to predict the residual strength of bridge columns.

In order to solve the practical problem faced in engineering reconnaissance. An artificial intelligence model was built to predict the damage image of bridge columns of different damage degrees. The damage images and damage index from the experimental database of bridge columns was first collected as input data. The GAN and CGAN

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models were applied to assist in the damage estimation of bridge column. The system would help engineers to evaluate the damage of bridge columns based on the predicted images without practical experience.

Methodology

Generative Adversarial Network

GAN is an artificial intelligence method for unsupervised learning. The basic architecture of GAN consists of two neural network as shown in Fig 1; one neural network called generator or generative model is responsible for generating fake data,; the other model called discriminator or discriminant model is responsible for identifying data. By competing with each other, fake data similar to the actual data can be generated to improve the model performance.

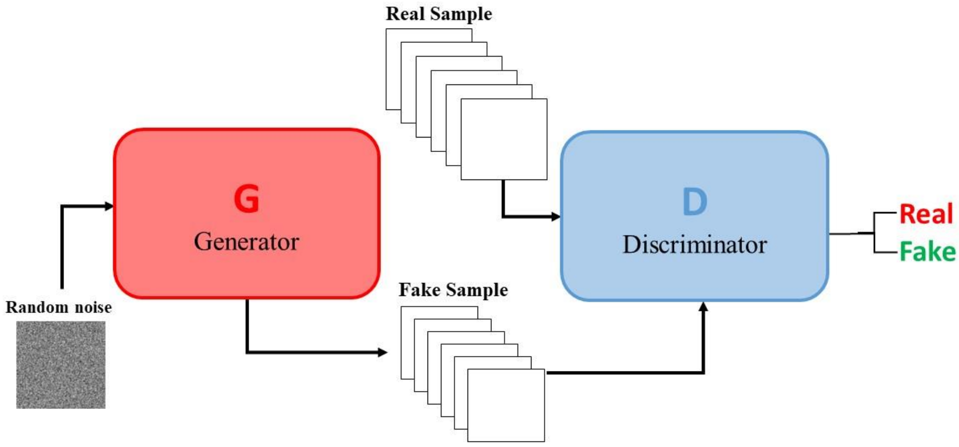


Fig 1 Generative Adversarial Network

The generative model produces new fake data based on the input real data and simulates the real data as closely as possible. The generated data will be treated as the real data and used as the input to the discriminant model simultaneously. To make the discriminator unable to distinguish the authenticity of the data, the generator continuously adjusts the learning parameter and improve the quality of the output data; Moreover, to distinguish the authenticity of the data, the discriminator continuously learns to improve the performance of the model. With the continuous competition between the generative and the discriminative model, the ability to generate and identify data of both models can be enhanced. Once the discriminator cannot identify the authenticity of the generated data, it means that the forged data by the generator is quite close to the real data, thereby the purpose of generating fake data close to the real data can be achieved.

The Generative Adversarial Network proposed by Goodfellow [11] first assumed a neural network model, named Generator (G), with a set of normally distributed data. A set of new distribution data, defined as P_G, is generated by the model and the actual sample data is P_{data}. The goal of the generator is to make the divergence of P_G and P_{data} as small as possible, Which can be described as:

$$G^{*} = \arg\min Div(P_G, P_{data}) \tag{1}$$

owever, as the divergence between P_G and P_{data} cannot be calculated, P_G and P_{data} are sampled to form a data set and input into a new neural network model, which is named as Discriminator (D). When the difference between the generated data and the real data becomes greater, the discriminator can distinguish the two easily, and the difference between the given scores will also be larger conversely. When the fake data is very similar to the real data, two very close scores will be given by the discriminator. An objective function to optimize the ability of the discriminator model is maximized to discriminate the data. The discriminator is expressed as:

$$D^{*} = \arg\max V(D,G) \tag{2}$$

V(D, G) is the objective function, which is defined as:

$$V(D,G) = E_{x\sim P_{data}(x)}[\log D(x)] + E_{z\sim P_{data}(z)}[\log(1 - D(G(z)))] \quad (3)$$

It can be seen that the objective function is obtained by summing two values. The first term $E_{x\sim Pdata(x)}$ takes the log of the discriminator D with the output of the real data x, and the second term $E_{z\sim Pdata(z)}$ estimates the difference between 1 and the output of the discriminator D with the data G(z) produced by the generator. If the recognition of the discriminator is good, D(x) will be larger and D(G(z)) will be smaller. Accordingly, logD(x) will increase and log(1-D(G(z))) will also increase. In addition, as the objective function V(D, G) has correlation with the data divergence[11], Equation 2 can be rewritten as:

$$G^{*}=\arg\min(\max V(D,G)) \quad (4)$$

By substitute Equation 3 into Equation 4

$$\min_{G}\max_{D} V(D,G) = E_{x\sim P_{data}(x)}[\log D(x)] + E_{z\sim P_{data}(z)}[\log(1 - D(G(z)))] \quad (5)$$

As indicated in Equation 5, the discriminator that maximizes the objective function, and the generator that minimizes this maximum should be found. Therefore, the generator and the discriminator continuously compete to each other to improve the performance, and to achieve the goal of generating data similar to the real data.

Image Database and CGAN Model setting

Damage images and damage index of rectangular bridge columns recorded in a series of experiments was collected to form the bridge column damage prediction database in this study. The database contains 140 bridge column failure images with 7 aspect ratios and 7 reinforcement ratios, respectively Those bridge images are depicted in Fig 2, and the aspect ratios and reinforcement ratios of bridges are shown in Table 1.

Table 1 Parameters of bridge columns

Name	Aspect ratio	Ratio of reinforcement(%)
C315	3	1.5
C307	3	0.75
C330	3	3.0
CLC	3.2	2.2
C615	6	1.5
C1015	10	1.5
C1S	3.22	1.9

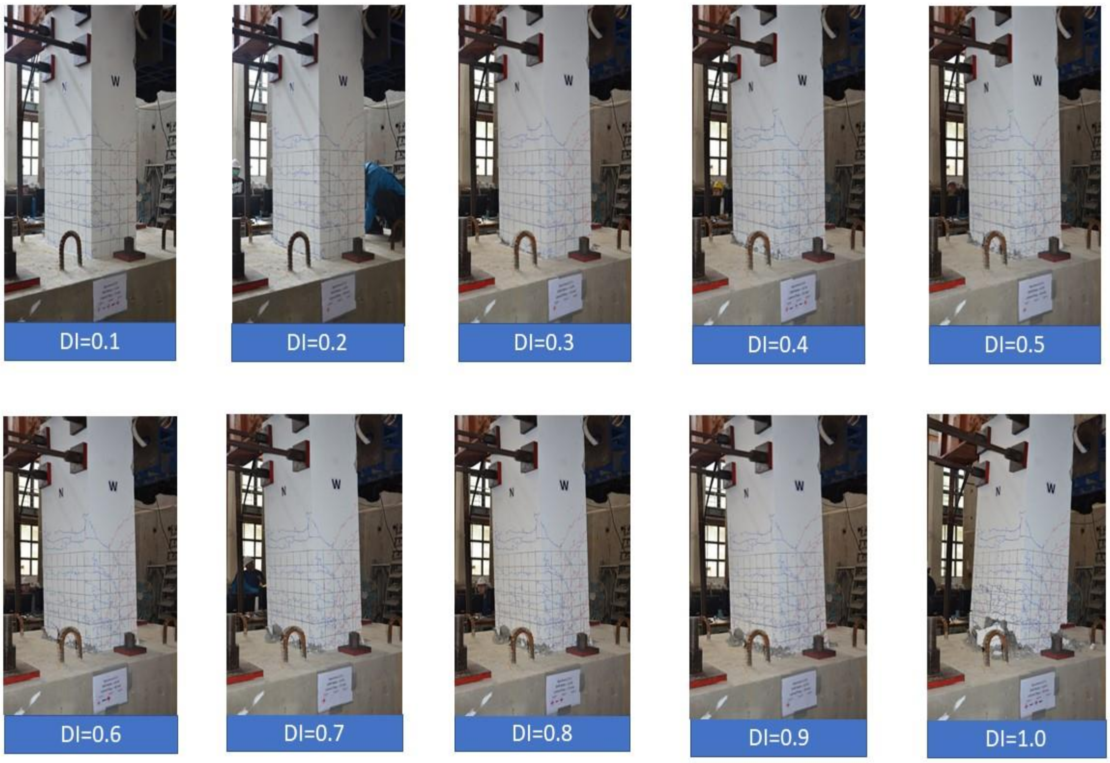


Fig 2 Bridge column images in database

Image Database

In order to make the output image change with the damage index, CGAN was further adopted to generate new bridge column damage images, and the input images of different processing methods were compared. The training process of CGAN model were divided into three stages, and the input images were continuously adjusted to optimize the image processing steps and image generation model.

In the third stage, the pixel size was adjusted to 28*28 and 28*56 images, which reduced the complexity of the model learning and facilitated the learning convergence. As the number of the original samples is limited, the random mask method shown in Fig 3 was applied to increase the number of samples of the input image for CGAN training. When the value of pixel was 0, it would be converted to 255; otherwise, when the pixel value was 255, it would be converted to 0. After the numerical transformation, white or black points were added to the original image.

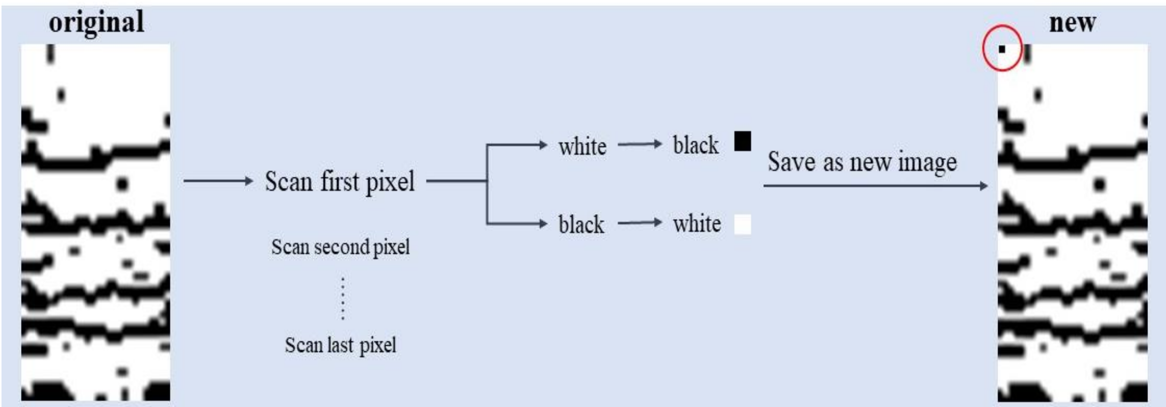


Fig 3 Random masking method

The sample images were rotated, translated, or occluded with a slight difference. The image was regarded as a new sample image to increase its total number. Since the new image generated by the model highly depend on the original input image, the image will be very different from the bridge image when rotation or translation is used. This adjustment benefits the model for making output images closer to the input images.

Fig 4 depicts the structure of the CGAN including a generative model and a discriminative model. The generative model consists of an input layer, two hidden layers, and an output layer. The input layer contains 256 neurons; the two hidden layers have 512 and 1024 neurons, respectively. Tanh function is set as the activation function of output layer. The discriminative model is also composed of an input layer, two hidden layers, and an output layer. The number of neurons in each layer of the input layer and the hidden layer is 512, and the sigmoid function is set as the activation function of the output layer. There are 2,297,120 parameters in the CGAN model.

Layer (type)	Output Shape	Param #
dense_12 (Dense)	(None, 256)	25856
leaky_re_lu_9 (LeakyReLU)	(None, 256)	0
batch_normalization_3 (Batch	(None, 256)	1024
dense_13 (Dense)	(None, 512)	131584
leaky_re_lu_10 (LeakyReLU)	(None, 512)	0
batch_normalization_4 (Batch	(None, 512)	2048
dense_14 (Dense)	(None, 1024)	525312
leaky_re_lu_11 (LeakyReLU)	(None, 1024)	0
batch_normalization_5 (Batch	(None, 1024)	4096
dense_15 (Dense)	(None, 1568)	1607200
reshape_1 (Reshape)	(None, 56, 28, 1)	0

Total params: 2,297,120
Trainable params: 2,293,536
Non-trainable params: 3,584

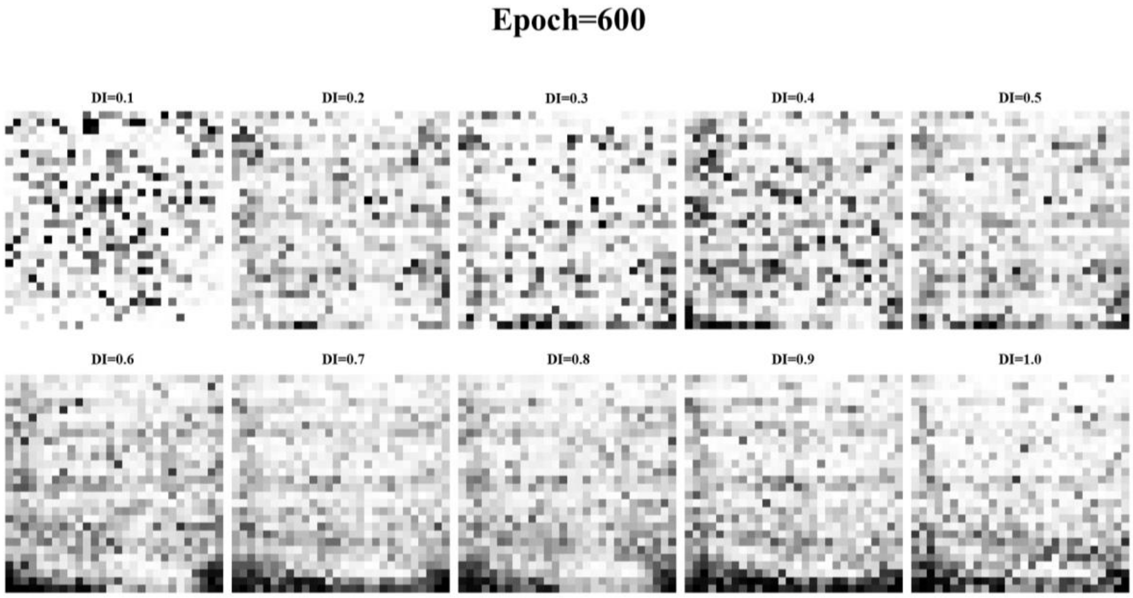
Fig 4 Structure of the CGAN model

Artificial Damage Image Generation

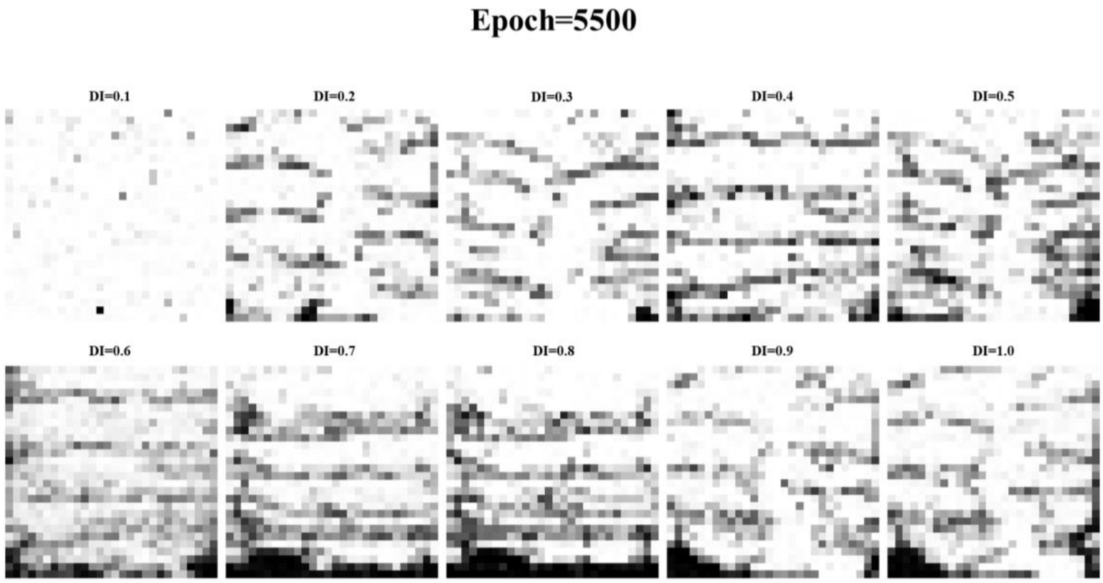
In order to generate artificial damage images of bridge columns with different damage index, the GAN model and CGAN model were established to generate new damage images. The size of input image of GAN were 180*180 and 100*200. On the other hand, the results of CGAN model were separated into three stages. The training results of GAN and CGAN models are described as follows:

The input image size of the first stage of CGAN training was 100*200, and three groups of training were included. The first group were grayscale images, and the number of input samples was 81; the second group were black-and-white images, and the number of input samples was also 81; the third group were modified black-and-white images, and the number of input samples was 170.

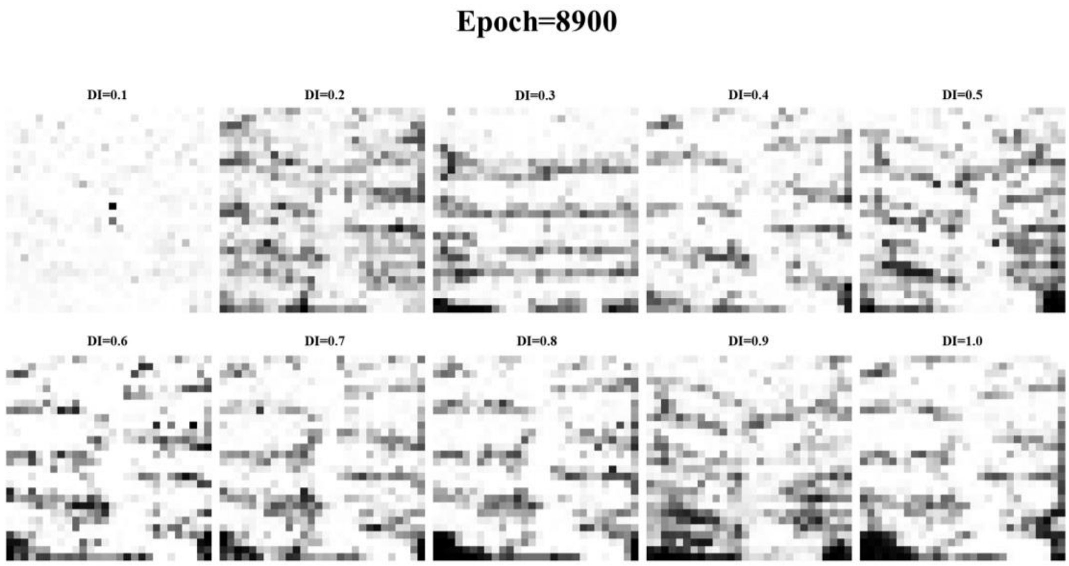
Therefore, in the third stage, the bridge column images were scaled into a pixel size of 28*28, and the number of samples was increased by random masking method. The 120 bridge column images were extended to 94080 images. **Fig 5** depicts the image of the new bridge column generated by the input of 28*28 images. Improved by the input images, the output images were slightly blurred, but it could roughly show white bridge columns and black cracks. Many noise black spots appeared on the output image were also produced at the bottom of the bridge column at the 600th epoch. With the increase of the number of epochs, the noise was gradually removed. At the 8900th epoch. The black cracks and a large area of black damage at the bottom of the bridge column could be clearly observed columns on the white background of the bridge columns.



(a) 600th epoch 28*28 output images



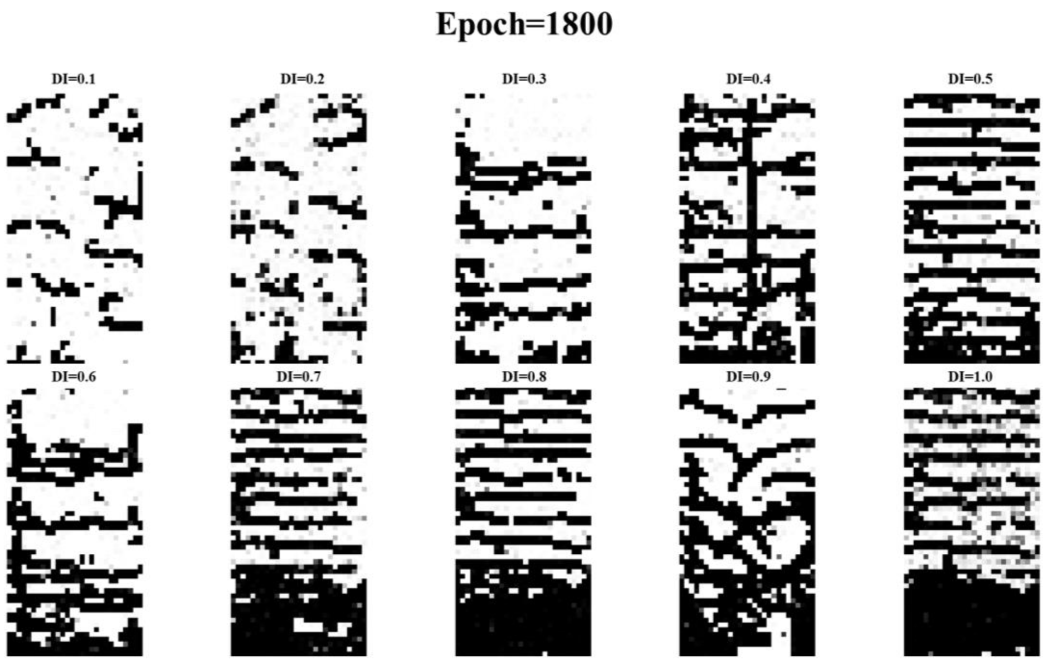
(b) 5500th epoch 28*28 output images



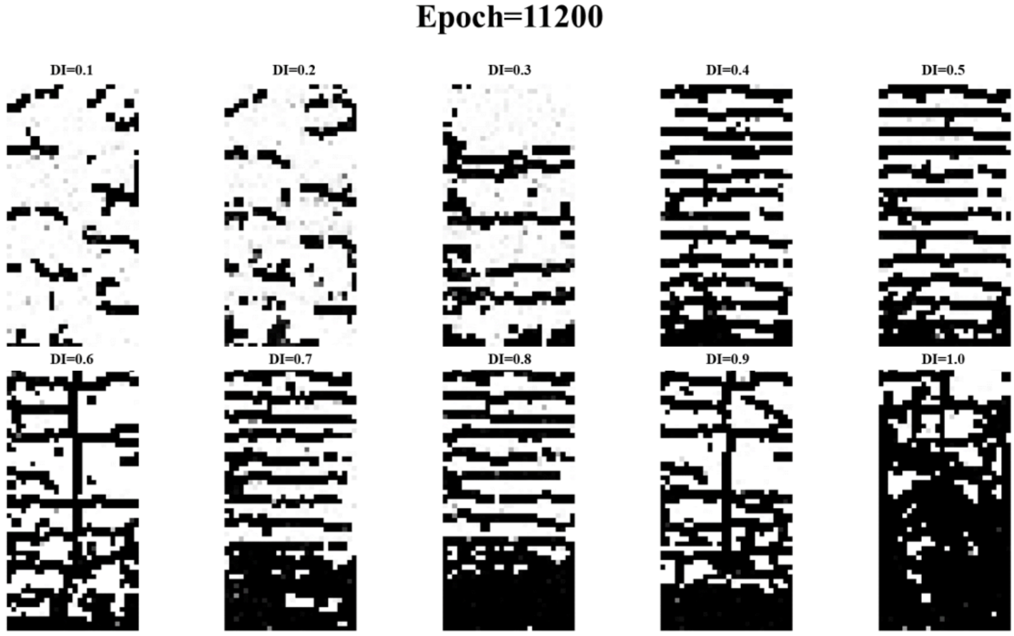
(c) 8900th epoch 28*28 output images

Fig 5 28*28 output images of CGAN in third stage

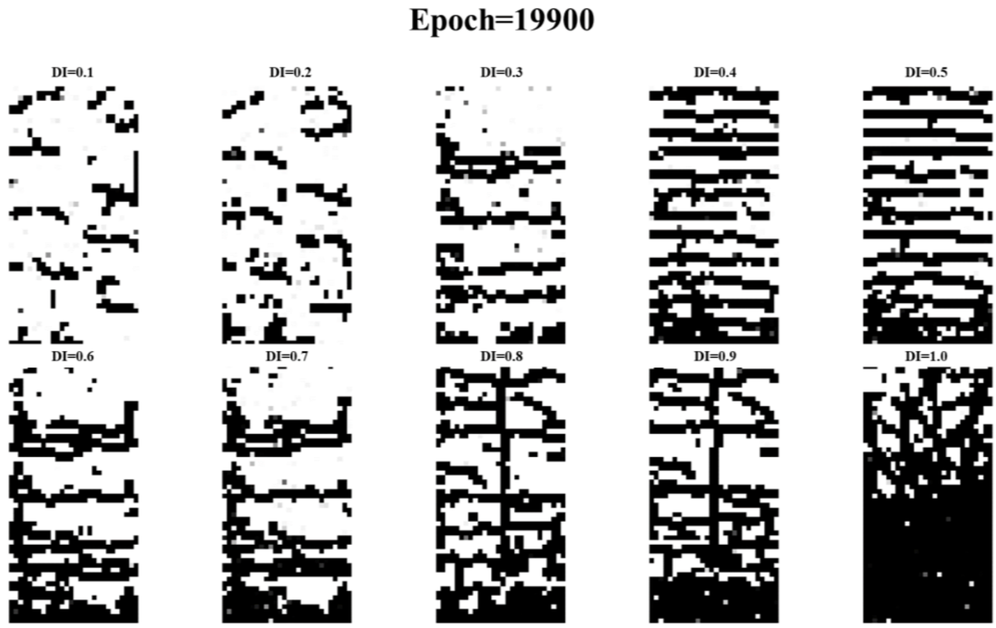
In order to make the generated image more similar to the real bridge column, the input sample was adjusted to pixel size of 28*56. Through the random mask method, the 150 sample images were increased to 117600. The final output images of the third stage were shown in Fig 6. This training was performed for 20,000 epochs. It could be found that black cracks of output images could be clearly observed whether epoch was small or large. There was almost no noise distribution in the images. The white background was very similar to the original bridge column, and the cracks extended from both sides to the center, which also conformed to the characteristics of the experimental bridge column images. The newly generated bridge images successfully imitated the large-scale damage at the bottom of the bridge columns. As the damage index increases, the number of cracks and the damage area at the bottom also increase.



(a) 1800th epoch 28*56 output images



(b) 11200th epoch 28*56 output images



(c) 19900th epoch 28*56 output images

Fig 6 28*56 output images of CGAN in third stage

Summary & Conclusions

In this study, artificial intelligence was used to generate bridge column damage images, and to predict the different degrees of damage that may occur to bridge columns. The damage images of the experimental bridge columns and the corresponding damage indexes were first collected to firm a bridge column damage database. GAN and CGAN models were applied. Bridge column damage images were set as input samples for models to generate bridge column images of different degrees of damage that might occur in the future.

As indicated by the result, the CGAN model can generate clearly bridge images to represent different damage indices. Output images could show cracks and large area damage of bridge columns obviously. With the increase of the damage index, the number of cracks in the bridge column and the damage area at the bottom also increase.

The possibility of applying artificial intelligence to bridge column seismic damage assessment of bridge column has been demonstrated in this study. The artificial intelligence-based system can be deployed practically to provide a reliable reference for damage reconnaissance.

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