Basavaraj Katageri[1], Rajashri Khanai[2], Rajkumar V. Raikar[1], Dattaprasad A. Torse[3], Krishna Pai[2]*

SURFACE CRACK DETECTION USING DEEP LEARNING FRAMEWORK FOR CIVIL STRUCTURES

OTKRIVANJE POVRŠINSKE PRSLINE UPOTREBOM OKRUŽENJA DUBOKOG UČENJA ZA GRAĐEVINSKE KONSTRUKCIJE

Originalni naučni rad / Original scientific paper
UDK /UDC:

Rad primljen / Paper received: 6.11.2021

Adresa autora / Author's address:
1) Department of Civil Engineering, Sheshgiri College of Engineering and Technology, Belagavi, India
2) Department of Electronics and Communication Engineering,. Sheshgiri College of Engineering and Technology, Belagavi, India *email: noureddine.menasri@univ-msila.dz
3) Department of Electronics and Communication Engineering, KLS Gogte Institute of Technology, Belagavi, India

Keywords
- convolutional neural network
- crack detection
- crack classification
- deep learning
- ReLU activation

Abstract

Civil structure crack detection solutions based on Artificial Intelligence (AI) have recently emerged as powerful tools with applications in complex structures where human detection considerably fails to detect the defect. The process of crack detection involves the collection of images from a wide range of infrastructure systems with diverse characteristics such as textures, conditions, and surface appearances. Considerable robustness of these processes is essential in defect detection models and need to be sufficiently robust to address these varied characteristics. In this paper, we propose civil structure crack detection using image classification in Deep Learning (DL) framework. The proposed framework uses the representational power of the convolutional layers of Convolutional Neural Network (CNN), which essentially selects appropriate features, and hence, eliminates the need for the complex feature extraction step. Additionally, good crack detection accuracy is obtained by the proposed framework at a significantly lower execution time. The proposed model consists of a total of 36 layers with 10 convolutional and transition layers connected. ReLU activation and Batch Normalization alongside dropout layers are added for better optimisation of the model. The image dataset consists of 40,000 images with 227×227 pixels with RGB channels. Images are auto resized to 28×28 before the training process in order to fit into the input layer. The image dataset is divided into 80 % for training and 20 % for testing. The proposed model achieved accuracy in the range of 88.21 to 98.60 %. We propose the hardware development of the model using Raspberry Pi™.

Ključne reči
- konvolucijske neuronske mreže
- otkrivanje prsline
- klasifikacija prsline
- duboko učenje
- ReLU aktivacija

Izvod

Rešenja za otkrivanje prslina u građevinskoj konstrukciji na bazi veštačke inteligencije (AI) odnedavno čine moćni alati za primenu u složenim konstrukcijama, gde čovekove mogućnosti značajno zaostaju. Postupak otkrivanja prsline podrazumeva prikupljanje snimaka iz širokog raspona infrastrukturnih sistema koji poseduju različite karakteristike kao što su teksture, uslovi okruženja, stanje površina. U ovim postupcima se zahteva izuzetna robusnost u modelima za otkrivanje grešaka, radi procesiranja ovih raznovrsnih karakteristika. U ovom radu predstavljamo otkrivanje prsline u građevinskoj konstrukciji primenom klasifikacije snimaka u okruženju dubokog učenja (DL). Predloženo okruženje koristi reprezentativnu moć konvolucijskih slojeva Konvolucijske Neuronske Mreže (CNN), koja u suštini pravi izbor odgovarajućih osobina, a time, eliminiše potrebu za složenim postupkom ekstrakcije. Pored toga, preciznost u otkrivanju prsline se postiže putem datog okruženja u znatno kraćem vremenu izvršenja. Predloženi model se sastoji iz ukupno 36 slojeva sa 10 konvolucijskih i prelaznih povezanih slojeva. ReLU aktivacija i Batch Normalization (beč normalizacija) pored izdvojenih slojeva se nadograđuju radi bolje optimizacije modela. Baza podataka snimaka se sastoji iz 40 hiljada snimaka od 227×227 piksela RGB tipa. Snimci se automatski svode na 28×28 pre procesa treniranja kako bi mogli da stanu u ulazni sloj. Baza snimaka se deli na 80 % za treniranje i 20 % za testiranje. Predloženi model postiže tačnost u rasponu od 88,21 do 98,60 %. Predlažemo hardverski razvoj modela korišćenjem Raspberry Pi™.

INTRODUCTION

Over the years, the civil structure starts to deteriorate due to dynamically changing environmental conditions, seismic activities, restoration /1/, underwater structures /2/, or due building materials. This structural deterioration affects the reliability, strength, and lifespan of the infrastructure. During deterioration crack formation is a very usual phenomenon. Cracks on structures can be specified as a complete or partial separation of the hardened concrete mixture into multiple parts. Early crack detection and recognition is important, because if cracks are detected at a very initial stage, then these cracks can be treated and cured. If these cracks are left unidentified, the infrastructure deteriorates rapidly. At present, crack detection is mainly done using manual observations and results in a few disadvantages such as long term observation, increased manpower, disturbing regular work, the safety of workers and error in detection of cracks. With the increase in construction work, it is difficult to achieve a crack detection target for large and complex structures. In order to improve the service level of large structures and to introduce automatic crack detection of civil structures, few researchers have proposed crack detection based on visual technology. However, due to the background of images, the detection rate is lower for diverse crack types. Therefore, we propose an image processing based crack detection system in the DL framework. DL as a subset of Artificial Intelligence (AI) is employed in the accurate detection and classification of real-time images of various civil structures.

Major contributions of this research are as follows. In this study, we introduce the model for automatic detection of civil structure cracks. The designed model enhances the discriminative features of the input image and suppresses noise in the image by filtering and smoothing, which can better extract discriminative information from images. There is no necessity for any kind of data de-noising or any other manual pre-processing operations. These operations may result in the loss of key information. This will help our model retain the information of the original image, and hence, improve working efficiency. The civil structure crack image /3, 4/ dataset is used to evaluate the model. In the further parts, we observe the results we obtain to demonstrate that our model has good performance. The main aim of this paper is to effectively detect and classify various crack types, few including intense, moderate, hair-line, horizontal, and vertical cracks. The rest of the paper is organised as: Section 2 provides literature survey; Section 3 introduces the proposed method and detailed experiment process; Section 4 demonstrates experimental results and their discussion; and Section 5 sums up the main points of our study.

LITERATURE SURVEY

Table 1 below shows the survey on all the types of implementation methodologies along with their accuracy which we carried out during the implementation of our network model. The main motivation for our work was after understanding the work carried out by authors /5, 6/.

The current literature review is based on the size of the dataset, type of DL network and its performance in terms of crack detection and classification accuracy. The outcome of each paper is mentioned in Table 1 to highlight benefits and shortcomings of each method, and based on these findings, we propose a novel DL model for enhancing the accuracy and algorithm speed.

The challenges in crack detection of civil structures from the existing body of knowledge are considered here. The main focus is on various implementations, methodologies, and their respective accuracies along with their outcomes to enhance the efficacy towards the development of the proposed model.

Table 1. Literature survey.

Dataset size	Model used	Accuracy/ precision	Outcomes obtained	Ref.
20,000	AlexNet	97.6% (A)	It has been reported that ResNet18 is better than VGGNet16 and also VGGNet16 is better than AlexNet, Author also projected the YOLOv3 model usage.	/7/
	VGGNet16	98.3% (A)		
	ResNet18	98.8% (A)		
98	LightGBM	99.7% (A)	Light gradient boosting Machine (LightGBM) as his proposed model is better than pix2pix models.	/8/
	Pix2pix	99.23% (A)		
40,000	CNN	98.22% (A)	Various Image processing techniques (IPTs), Canny edge detection and Sobel edge detection.	/9/
3,500	VGG16	92.27% (A)	To enable AI models to evolve, a feedback system with corrections from an expert in the field of inspections is crucial, as stated by the author.	/10/
60,000	VGG16	88.0% (A)	Detailed demonstration on various types of Deep Learning networks along with their metrics was demonstrated by the author.	/11/
	ResNet34	91.6% (A)		
	ResNet50	86.5% (A)		
	DenseNet121	92.4% (A)		
	DenseNet169	89.9% (A)		
	InceptionV3	88.4% (A)		
	MobileNet	95.3% (A)		
	MobileNetV2	89.7% (A)		
500	SVM	81.12% (P)	A model for Road Crack detection and made it work on the Smartphone device.	/3/
	Boosting	73.60% (P)		
	ConvNets	86.96% (P)		
225	Back-propagation neural network	92% (A)	Algorithms and optimization architecture using varieties of flowcharts.	/11/
800	T-DCNN pre-classification	84.7% (P)	Sealed crack detection, CrackIT, CrackForest, and Canny edge detection methods were the topic on which the author did a comparative study.	/12/
1,330	Faster R-CNN	69% (P)	Wall-climbing unmanned aerial system (UAS) model for crack detection on walls.	/13/
	SSD-MobileNetV1	49% (P)		
	SSD-MobileNetV2	52% (P)		
	SSDLite-MobileNetV2	52% (P)		

TYPES OF CRACKS

Intense crack: the cracks are very easy to identify as they are common and easily identifiable and need instant repairs and cure as they are most dangerous. These cracks are formed due to continuous pressure or activity on the surface. Intense crack formation is usually found on concrete roads, walls, dams, and other civil structures. The accuracy of recognising *Intense crack* is around 95 %, /2/. To identity intense cracks K-means clustering, adaptive tensor voting, minimum and spanning tree methods can be employed, /14/. These methods maintain accuracy of around 93.3 %.

Sub-way tunnel cracks can be also classified as *Intense cracks*. Support Vector Machine (SVM), Radial Basis Function Neural Network (RBF), morphological operation, Extreme Learning Machines (ELM), thresholding operation and k-nearest neighbours algorithm (KNN) are another few of the methods used by the author /15/ for detection and classification of cracks leading to an accuracy of 90 %.

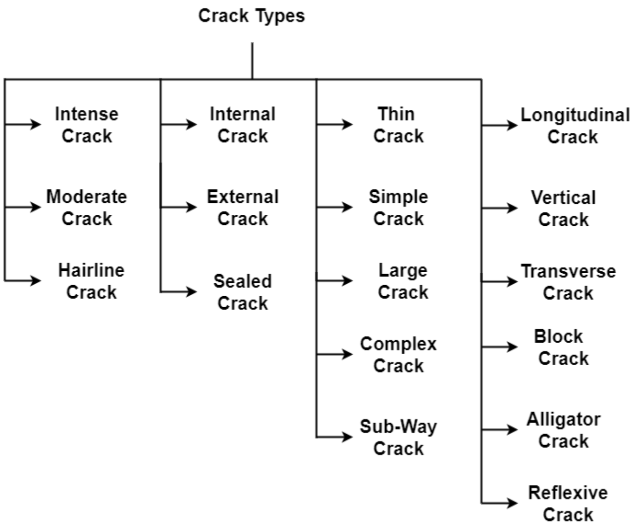

Figure 1. Types of cracks.

Figure 1 shows various types of cracks on civil structures.

Moderate crack: these types of cracks are similar to that of intense cracks, but the intensity of the crack is lesser as compared to that of *intense crack*. Moderate cracks are common but are not so very easy to identify. Even these types of cracks need instant repairs and curing. Crack formation is usually found on concrete roads, walls, dams, and other civil structures. The accuracy of recognising moderate crack has been reported around 93 %, /2/. Moderate cracks have a common occurrence in the regions of underwater dams and under pavement surfaces. These regions are hard to access and are difficult to detect for cracks. Hence, the author /14/ proposed the method of adaptive tensor voting along with K-means clustering and minimum spanning tree for moderate crack detection.

Hairline crack: these types of cracks are very hard to identify as they are very thin compared to the size of moderate cracks. Hairline crack formation is the initial stage of any crack formation. These cracks are usually formed due to continuous pressure or an improperly built civil structure. Hairline cracks are very difficult to classify or detect in underwater structures, hence, sonar images are used /14/. The accuracy of recognising hairline crack is around 86 %. Plastic surfaces are highly prone to hairline cracks. An approach using image processing and optimisation to measure the quality of binarization has been proposed by the author /16/. It has been reported that this approach performed better than Otsu's method and clustering.

Internal crack: due to a small degree of contraction or expansion of build materials in the civil structure due to seasonal changes, or due to the poor structural or poor initial foundation issues, there might be the formation of internal cracks inside the building material. These cracks are highly isolated and hard to locate. The accuracy of detection or classification of such a crack is very low in a general methodological way. Some high-end methods such as RFID tags, electrically conductive materials, sonar sensors, etc. /14, 17/ have been used for internal crack detection.

External crack: external cracks are traditionally formed due to seismic and restoration activates as mentioned by the author in his case study of Netherlands buildings /1/. These types of cracks are visible on the surface of the civil structure. Hence, they are quite painless to detect, classify, and thus make way towards higher accuracy. External hairline cracks are very common in RC bridges. These cracks have been detected by using the optical flow analysis method along with the stereo triangulation technique and least square methods, /18/.

Sealed crack: the process in which cracks on civil structures, like pavements or walls, are sealed with an aid of adhesive sealant and treatments, is called *crack sealing*. These kinds of cracks are not completely hidden or visible. Such a type of crack detection and classification can be done using transfer learning-based pre-classification and obtaining an accuracy of 95.3 %, /12/. Methods like segmentation, thresholding and/or morphological operations can be carried out. These methods have produced a higher and consistent level of accuracy, /19/. A precision of 98 % along with an accuracy of 93 % is observed.

Longitudinal crack: due to interchanging contraction and expansion in building materials over the temperature change and also due to insufficient protection from heat, longitudinal cracks are formatted. There can be an internal, external, intense, or moderate type of crack. They are most dangerous and immediate treatment and repairs are needed. Longitudinal cracks, alligator cracks, and/or reflexive cracks can be predicted by using Support Vector Machine (SVM), /20/. Hence, in the case of pavement cracks, an accuracy of 82 % is obtained by the use of the Fuzzy clustering method, /21/. The fuzzy clustering method is very useful when the input regions of the images are blurry and not precisely defined.

Vertical crack: in conditions such as improper provision for the expansion of building materials, the two expanded building materials exert intense pressure on the surface of each other. Hence, the formation of vertical crack begins. Proper planning, orientation and treatment are required to avoid such cracks. Such cracks can be easily detected and classified by using one of the methods named Min-Max Gary Level Discrimination (M2GLD), /22/. Civil structures such as bridges, buildings, pavements, and roads are common for vertical cracks. These types of cracks can be detected by methods such as Support Vector Machine (SVM), Sobel edge detection method, morphological operation, Empirical Mode Decomposition (EMD), random forest, thresholding operation, k-nearest neighbours algorithm (KNN) and K-Dimensional Tree /19, 23, 24/. These methods are highly adaptable for 2-D or 3-D crack detection.

PROPOSED MODEL

The proposed experimental model, shown in Fig. 2, encompasses 5 phases of operation: (1) image acquisition; (2) image processing; (3) designing and network implementation; (4) training the model; (5) crack detection and validation. A detailed description of these phases is mentioned below.

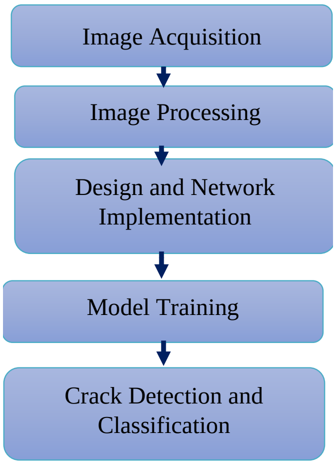

Figure 2. Phases of operation.

IMAGE ACQUISITION

The proposed model is initially trained with an image dataset then tested with some random images from the data. The image dataset is taken from /3, 4/ consisting of a total of 40,000 images. The dataset consists of two folders: *Cracked Condition* and *Un-Cracked Condition*. These two folder names will later be assigned as our two image recognition and classifying classes. The Cracked Condition and Un-Cracked Condition folder consist of 20,000 images each. Images are 227×227 pixels with RGB channels. The dataset is generated from 458 high-resolution images (4032×3024 pixels) with the method proposed by Zhang et al. /3/. Few samples of the dataset are shown in Figs. 3 and 4. Future work will be more concentrated on accessing input images to our network model through a camera, or UAV camera /6/ etc.

In the present work, we describe the utilised datasets in three categories as training, validation, and test sets. The base dataset is from walls and floors of several concrete buildings in METU Campus and the dataset is publicly shared for research work. These images are occupied from the structures with the camera in front of, directly to the structure, approximately 1 m distance. The image capture procedure follows the condition of a single day capture with comparable illumination conditions. However, the concrete surfaces vary in terms of surface finishes, /3/.

IMAGE PROCESSING

The image is analysed and visualized to check if there is any need for restoration or enhancement to be applied to it. Image segmentation and Region of Interest /23, 24/ also can be carried out in this stage alongside image cleaning, as shown in Fig. 5.

The above-used filter is called a Canny Edge Detection Filter when a Gaussian filter of the size, say $(2k + 1)\times(2k + 1)$ is applied to a smoothened image. This helps us in finding

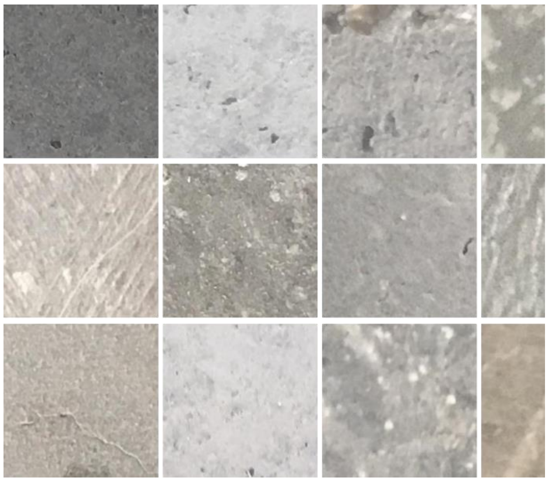

Figure 3. Images of un-cracked condition category.

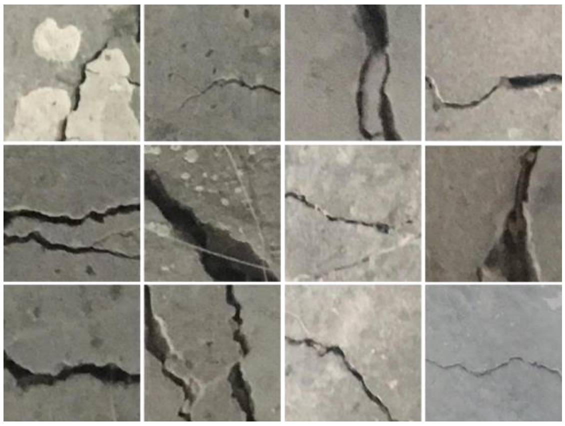

Figure 4. Images of cracked condition category.

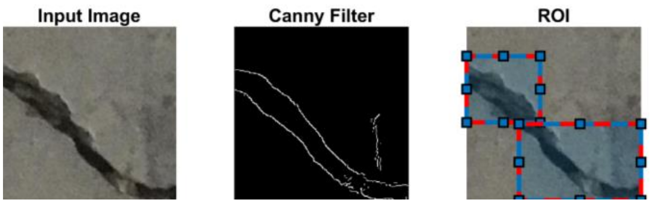

Figure 5. Edge detection and region of interest on intense type of cracks.

the intensity gradients of the image so that the further process of edge detection can be carried out. The smoothened image is used to reduce the noise present in the image. The equation of Gaussian filter can be stated as for above-mentioned size as in the Eq.(1):

$$H_{ij} = \frac{1}{2\pi\sigma^2}\left\{-\frac{[i-(k+1)]^2+[j-(k+1)]^2}{2\sigma^2}\right\},\ i \geq 1, j \leq (2k+1) \quad (1)$$

Apart from canny filters, Sobel filter, or Gabor filter /23, 25/ can also be used. All the input images get resized to 28×28×3 as input size of images. *Min-max grey level enhancement, Otsu-based image thresholding* /22/, and followed by *image cleaning* are optional enhancements that can be added to our proposed model. For more accurate detection and making this system compatible for almost all types of environments, additional image processing techniques can be employed, such as IR-based, Ultrasonic, Laser TOFD, SEM, or video images, /6/.

DESIGN AND NETWORK IMPLEMENTATION

The proposed model we developed is an inspiration from the pre-built model such as AlexNet, VGGNet16, and Res Net18. So, we referred to multiple research works and tried to understand the Network implementations.

Therefore, after the survey was done on various Training Models, we began to implement our proposed model. The tool used was MATLAB/Simulink R2021b along with Deep Network Designer and Classification Learner app. The implementation steps are as mentioned below.

Step 1: developing a Vanilla network

Feature extraction is a very crucial step needed to be performed on any data so that any form of raw data can be easily managed for further processing. Hence, the receptive field is considered while designing the architecture of a network. Keeping in mind that the size of the object should be equal to the size of the receptive field as we move to the end of the model, the designing of network architecture is initiated. The required receptive field can be obtained by placing the adequate amount of convolution blocks paired with transition blocks.

Step 2: ending the network

After all adequate amount of convolution blocks paired with transition blocks are placed in order, the output obtained is flattened. This is done to simplify the multi-dimensional input tensors into a single dimension output. Also, softmax activation is employed after flattening the output. This activation layer function helps the neural network predict a multinomial probability-like distribution.

Usually, loss of data is seen when it is observed a transition block is used. This is due to the pooling layer present in the transition layer. Hence, transition later is not applied as we move toward the end of the network.

Step 3: optimisation of the network

Reduction in a filter inside the convolution layers: reducing the size/number of filters inside the 1×1, 3×3, or 5×5 convolution layers will substantially reduce the parameters in all the layers.

Determining an optimal Learning rate

Change in *Learning rate* will proportionally affect the fitting of the network. For example, the risk of overfitting will drastically increase with a smaller learning rate.

Adding *Batch normalisation layers*: during the training of the deep networks, standardisation of data is very important. Hence, Batch normalisation simply standardizes the inputs obtained to a layer considering each mini size of batch assigned, as shown in Fig. 6.

Adding *Dropout layers*: this layer plays a very important role in avoiding the network model from overfitting. The desired probability value is set, and the layer randomly sets the neurons to zero at each training phase.

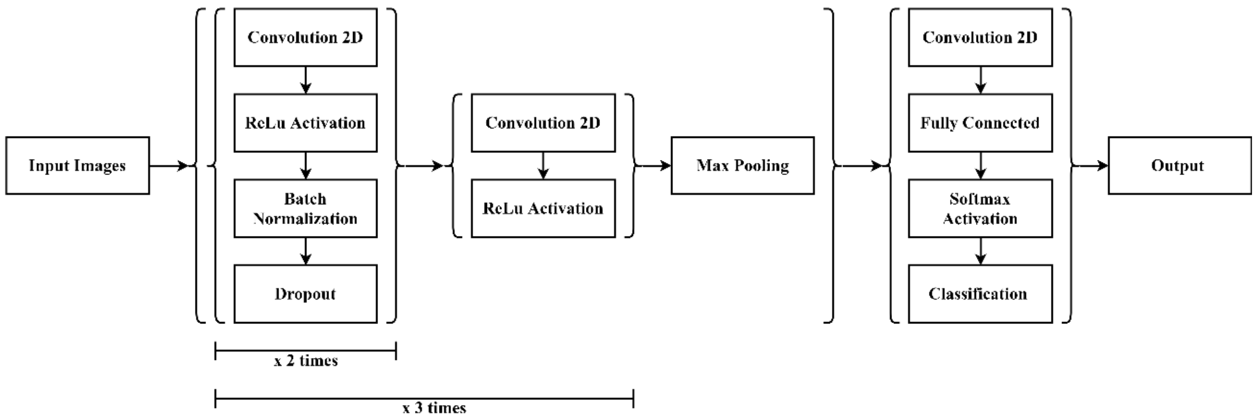

Figure 6. Proposed network model.

Training the model

The proposed model is trained using 32,000 images and validated using 8,000 images. Images are auto resized to 28×28×3 by Deep Learning Network app. Table 2 mentions the entire training configuration used during model training.

Table 2. Proposed network training configuration.

Particulars	Values
Number of images	40,000
Number of classes	2
Solver	Adam
Max epochs	30
Mini batch size	1024
Execution environment	GPU
Max iterations	930

Hence, the trained model is saved as a .mat file. This trained model is then used for deploying in hardware, such as Raspberry Pi™. Even the deployment of the trained model may be done on a smartphone, /3/. Also, the same trained model can be used for transfer learning /12/ applications to benefit crack detection in various other environments.

The proposed network model is run on a laptop with an Intel i5 processor, 8 GB RAM, and Nvidia GPU GeForce MX130 with 2 GB.

RESULTS AND DISCUSSIONS

To validate and test our network model, we trained the model with a 32,000 image dataset and thereafter used an 8,000 image dataset for validation. Here we trained and validated our proposed model with variation in Learning Rate, Dropout Probability, Batch size and Epochs. One of such variation output is shown in Tables 3 and 4, followed by plots in Figs. 7 and 8.

Table 3. Training and validation for dropout probability 0.5.

Initial learning rate	Training time	Accuracy	Loss
0.01	17 min 36 sec	88.21%	0.52
0.05	17 min 24 sec	88.25%	0.49
0.10	16 min 16 sec	88.54%	0.45
0.30	14 min 04 sec	88.96%	0.44
0.50	12 min 19 sec	89.76%	0.41

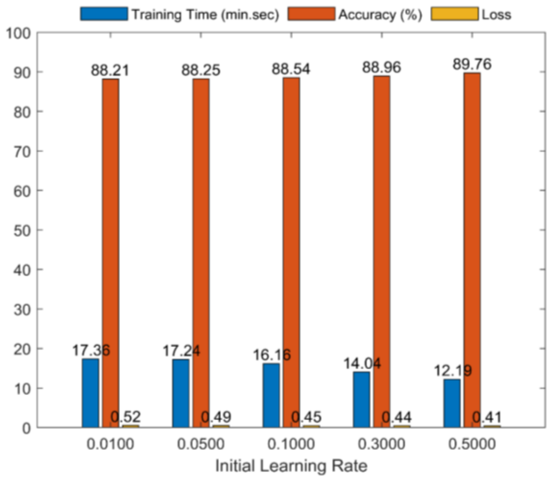

Figure 7. Plot of metrics for dropout probability 0.5.

Table 4. Training and validation for dropout probability 0.2.

Initial learning rate	Training time	Accuracy	Loss
0.01	32 min 32 sec	92.57%	0.29
0.05	29 min 53 sec	94.34%	0.28
0.10	26 min 22 sec	95.21%	0.23
0.30	24 min 56 sec	97.07%	0.19
0.50	23 min 46 sec	98.60%	0.12

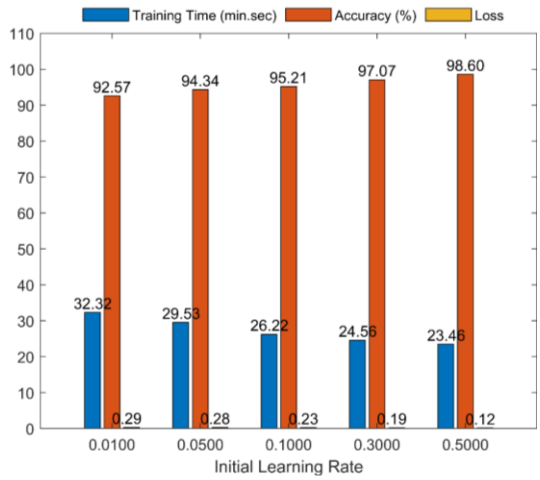

Figure 8. Plot of metrics for dropout probability = 0.2.

As shown in Figs. 7 and 8, we can infer that as the learning rate is increasing, the proposed model's training time is reduced, also the accuracy is increasing.

The performance of the proposed network is evaluated based on values of accuracy defined as in Eq.(2):

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}, \tag{2}$$

where: TP, TN, FP, and FN correspond to true positive, true negative, false positive, and false negative, in respect. Hence, we obtain the proposed network model accuracy in the range of 88.21 to 98.60 % over repeated training for a given configuration, as shown in Table 5. Results in the form of GUI outputs displayed to the user are as shown in figures below. The user can choose the image which we want to process, and the output will be as shown below in Fig. 9.

Table 5. Survey of various training models with accuracy.

Types used	Accuracy	References
AlexNet	97.6%	/7/
VGGNet16	98.3%	
ResNet18	98.8%	
LightGBM	99.7%	/8/
Pix2pix	99.23%	
CNN	98.22%	/9/
VGG16	92.27%	/10/
VGG16	88.0%	/5/
ResNet34	91.6%	
ResNet50	86.5%	
DenseNet121	92.4%	
DenseNet169	89.9%	
InceptionV3	88.4%	
MobileNet	95.3%	
MobileNetV2	89.7%	
Proposed Model	98.60%	

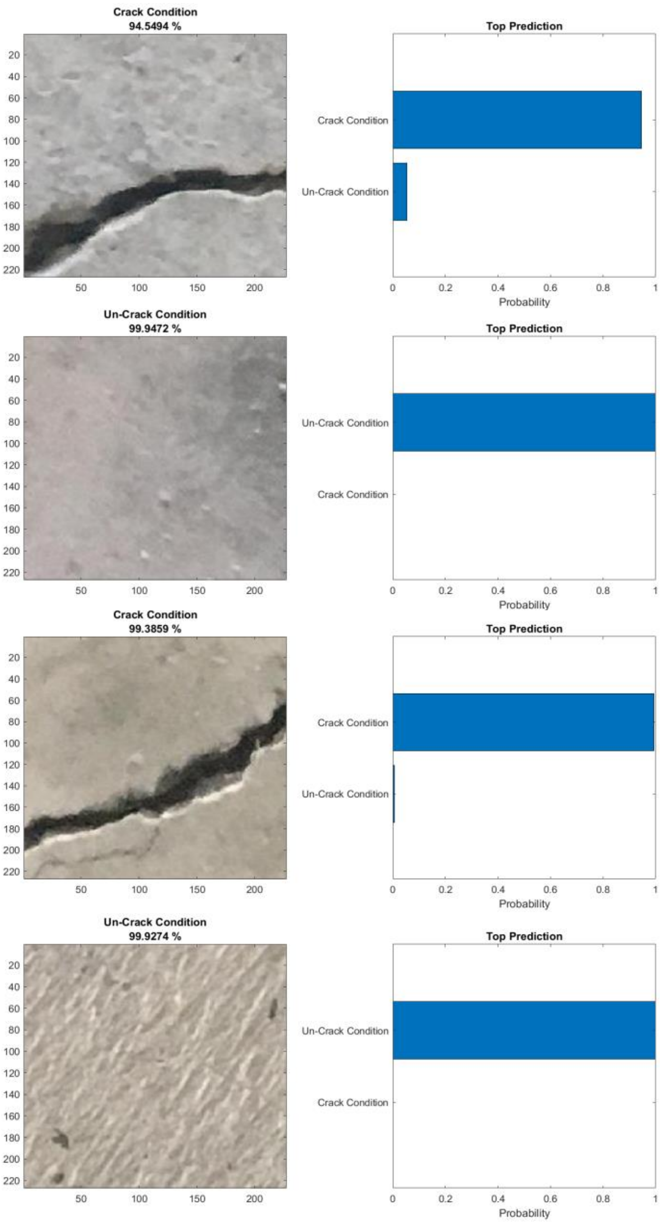

Figure 9. Results of the Input images from User.

CONCLUSION AND SCOPE OF FUTURE WORK

The safety of any civil structure is of high importance. Early detection and classification of structural cracks can save a large number of mishaps. Research work in this domain is one of the critical areas in the field of object detection. The detailed features of the crack require advanced feature extraction techniques to improve model detection accuracy. The experimental results show that the detection accuracy of CNN models varies in the range of 88.21 to 98.60 %. The shortest time-consuming model only needs 0.0133 seconds to detect 28×28 pixels. Therefore, if we pay attention to the detection rate in the actual project, we can choose to use ResNet18. If we need to consider both the detection rate and detection efficiency, we can choose the proposed 36 layered models. This model is trained using 32,000 images and validated using the rest of 8,000 (20 %) images. Hence, the 36 layered trained network model not only detects and classifies the images as Crack or Un-cracked, but also can be deployed on any of the hardware that can support DL, i.e. hardware such as Raspberry Pi™, or smart phones.

REFERENCES

1. Bal, İ.E., Dais, D., Smyrou, E., Sarhosis, V. (2021), *Monitoring of a historical masonry structure in case of induced seismicity*, Int. J Archit. Herit., 15(1): 187-204. doi: 10.1080/15583058.2020.1719230
2. Sheerin Sitara, N., Kavitha, S., Raghuraman, G. (2018), *Review and analysis of crack detection and classification techniques based on crack types*, Int. J Appl. Eng. Res. 13(8): 6056-6062. doi: 10.37622/IJAER/13.8.2018.6056-6062
3. Zhang, L., Yang, F., Zhang, Y.D., Zhu, Y.J. (2016), *Road crack detection using deep convolutional neural network*, IEEE Int. Conf. Image Process. (ICIP), Phoenix, AZ, USA, 2016, pp. 3708-3712. doi: 10.1109/ICIP.2016.7533052
4. Özgenel, Ç.F., Gönenç Sorguç, A. (2018), *Performance comparison of pretrained convolutional neural networks on crack detection in buildings*, ISARC 35th Int. Symp. Autom. Robot. Constr. Berlin, Germany, 2018, pp.693-700. doi: 10.22260/isarc2018/0094
5. Dais, D., Bal, İ.E., Smyrou, E., Sarhosis, V. (2021), *Automatic crack classification and segmentation on masonry surfaces using convolutional neural networks and transfer learning*, Autom. Constr. 125: 103606. doi: 10.1016/j.autcon.2021.103606
6. Mohan, A., Poobal, S. (2018), *Crack detection using image processing: A critical review and analysis*, Alexandria Eng. J, 57(2): 787-798. doi: 10.1016/j.aej.2017.01.020
7. Yang, C., Chen, J., Li, Z., Huang, Y. (2021), *Structural crack detection and recognition based on deep learning*, Appl. Sci. 11(6): 2868. doi: 10.3390/app11062868
8. Jo Chun, P., Izumi, S., Yamane, T. (2021), *Automatic detection method of cracks from concrete surface imagery using two-step light gradient boosting machine*, Comput. Aided Civ. Infrastr. Eng. 36(1): 61-72. doi: 10.1111/mice.12564
9. Cha, Y.J., Choi, W., Büyüköztürk, O. (2017), *Deep learning-based crack damage detection using convolutional neural networks*, Comput. Aided Civ. Infrastr. Eng. 32(5): 361-378. doi: 10.1111/mice.12263
10. da Silva, W.R.L., de Lucena, D.S. (2018), *Concrete cracks detection based on deep learning image classification*, Proc. 2(8): 489. doi: 10.3390/icem18-05387
11. Moon, H.G., Kim, J.H. (2011), *Intelligent crack detecting algorithm on the concrete crack image using neural network*, Proc. 28th Int. Symp. Autom. Robot. Constr. ISARC, South Korea, 2011, pp.1461-1467. doi: 10.22260/isarc2011/0279
12. Zhang, K., Cheng, H.D., Zhang, B. (2018), *Unified approach to pavement crack and sealed crack detection using preclassification based on transfer learning*, J Comput. Civ. Eng. 32(2): 04018001. doi: 10.1061/(asce)cp.1943-5487.0000736
13. Jiang, S., Zhang, J. (2020), *Real-time crack assessment using deep neural networks with wall-climbing unmanned aerial system*, Comput. Aided Civ. Infrastr. Eng. 35(6): 549-564. doi: 10.1111/mice.12519
14. Shi, P., Fan, X., Ni, J., et al. (2017), *A novel underwater dam crack detection and classification approach based on sonar images*, PLoS One, 12(6): e0179627. doi: 10.1371/journal.pone.0179627
15. Zhang, W., Zhang, Z., Qi, D., Liu, Y. (2014), *Automatic crack detection and classification method for subway tunnel safety monitoring*, Sensors, 14(10): 19307-19328. doi: 10.3390/s141019307
16. Liu, H., Huang, Z., Zang, Y., Talab, A.M.A. (2016), *Shape-based micro crack detection in plastic through image processing*, Int. J Sign. Proc. Image Proc. Patt. Recog. 9(1): 281-288. doi: 10.14257/ijsip.2016.9.1.27
17. Morita, K., Noguchi, K. (2008), *Crack detection methods using radio frequency identification and electrically conductive materials*, In: Proc. 14th World Conf. Earthq. Eng., vol.6932, 69320Q, San Diego, CA, USA, 2008. doi: 10.1117/12.775967
18. Yang, Y.-S., Yang, C.-M., Huang, C.-W. (2015), *Thin crack observation in a reinforced concrete bridge pier test using image processing and analysis*, Adv. Eng. Softw. 83: 99-108. doi: 10.1016/j.advengsoft.2015.02.005
19. Kamaliardakani, M., Sun, L., Ardakani, M.K. (2016), *Sealed-crack detection algorithm using heuristic thresholding approach*, J Comput. Civ. Eng. 30(1): 04014110. doi: 10.1061/(asce)cp.1943-5487.0000447
20. Chen, Y., Mei, T., Wang, X., Li, F., et al. (2016), *A bridge crack image detection and classification method based on a climbing robot*, J Univ. Sci. Technol. China, 46(9): 788-796. doi: 10.3969/j.issn.0253-2778.2016.09.011
21. Ahmed, N.B.C., Lahouar, S., Souani, C., Besbes, K. (2017), *Automatic crack detection from pavement images using fuzzy thresholding*, Int. Conf. Control. Autom. Diagnosis (ICCAD) 2017, Hammamet, Tunisia, pp.528-537. doi: 10.1109/CADIAG.2017.8075714
22. Hoang, N.D. (2018), *Detection of surface crack in building structures using image processing technique with an improved Otsu method for image thresholding*, Adv. Civ. Eng. 2018. doi: 10.1155/2018/3924120
23. Lins, R.G., Givigi, S.N. (2016), *Automatic crack detection and measurement based on image analysis*, IEEE Trans. Instrum. Meas. 65(3): 583-590. doi: 10.1109/TIM.2015.2509278
24. Li, W., Huyan, J., Tighe, S.L., et al. (2017), *Three-dimensional pavement crack detection algorithm based on two-dimensional empirical mode decomposition*, J Transp. Eng. Part B Pavements, 143(2): 04017005. doi: 10.1061/jpeodx.0000006
25. Salman, M., Mathavan, S., Kamal, K., Rahman, M. (2013), *Pavement crack detection using the Gabor filter*, In: Proc. 16th Int. IEEE Conf. Intell. Transp. Syst. (ITSC 2013), The Hague, Netherlands, 2013, pp. 2039-2044. doi: 10.1109/ITSC.2013.6728529

© 2023 The Author. Structural Integrity and Life, Published by DIVK (The Society for Structural Integrity and Life 'Prof. Dr Stojan Sedmak') (http://divk.inovacionicentar.rs/ivk/home.html). This is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License