Smart Structures and Systems, *Vol. 24, No. 5 (2019) 567-585*
DOI: https://doi.org/10.12989/sss.2019.24.5.567

A review on deep learning-based structural health monitoring of civil infrastructures

X.W. Ye*, T. Jin[a] and C.B. Yun[b]

Department of Civil Engineering, Zhejiang University, Hangzhou 310058, China

(Received June 23, 2019, Revised August 25, 2019, Accepted August 30, 2019)

Abstract. In the past two decades, structural health monitoring (SHM) systems have been widely installed on various civil infrastructures for the tracking of the state of their structural health and the detection of structural damage or abnormality, through long-term monitoring of environmental conditions as well as structural loadings and responses. In an SHM system, there are plenty of sensors to acquire a huge number of monitoring data, which can factually reflect the in-service condition of the target structure. In order to bridge the gap between SHM and structural maintenance and management (SMM), it is necessary to employ advanced data processing methods to convert the original multi-source heterogeneous field monitoring data into different types of specific physical indicators in order to make effective decisions regarding inspection, maintenance and management. Conventional approaches to data analysis are confronted with challenges from environmental noise, the volume of measurement data, the complexity of computation, etc., and they severely constrain the pervasive application of SHM technology. In recent years, with the rapid progress of computing hardware and image acquisition equipment, the deep learning-based data processing approach offers a new channel for excavating the massive data from an SHM system, towards autonomous, accurate and robust processing of the monitoring data. Many researchers from the SHM community have made efforts to explore the applications of deep learning-based approaches for structural damage detection and structural condition assessment. This paper gives a review on the deep learning-based SHM of civil infrastructures with the main content, including a brief summary of the history of the development of deep learning, the applications of deep learning-based data processing approaches in the SHM of many kinds of civil infrastructures, and the key challenges and future trends of the strategy of deep learning-based SHM.

Keywords: structural health monitoring; deep learning; convolutional neural network; structural damage detection; structural condition assessment; artificial intelligence; machine learning; computer vision

1. Introduction

The structural health monitoring (SHM) of civil infrastructures mainly aims to monitor the structural condition, detect the structural damage/abnormality, and evaluate the structural safety based on the long-term monitoring data from a variety of sensors installed on the structure. It is a cutting-edge and multi-disciplinary technology acting as a powerful tool for improving and upgrading the level of intelligent maintenance and management of civil infrastructures (Ni *et al.* 2010, Ni *et al.* 2012, Ye *et al.* 2012, Hakim and Razak 2014). In addition, the comprehensive understanding of in-service structural performance and behavior under realistic environmental and loading conditions will benefit from the long-term monitoring of a civil engineering structure (Ye *et al.* 2013, Ye *et al*. 2015, Ye *et al*. 2016a,b,c, Dong *et al*. 2018).

Although many kinds of SHM systems have been designed and implemented on many kinds of civil infrastructures and a huge amount of monitoring data has been obtained in the past two decades, a big gap still exists between SHM and structural maintenance and management (SMM). One of the main reasons is that the current data processing methods are confronted with challenges from environmental noise, the volume of measurement data, the complexity of computation, etc., which severely constrains the pervasive application of SHM technology (Kesavan *et al*. 2005, Matos *et al*. 2009). Realization of the autonomous, accurate and robust processing of the monitoring data has been a great concern of the SHM community (Gao and Spencer 2007, Jang *et al*. 2010, Min *et al*. 2010, Cho *et al*. 2015, Sony *et al*. 2019).

With the arrival of the fourth revolution of science and technology, the technology of artificial intelligence (AI) is subversively renovating the activities of human life and social production (Weng *et al*. 2001). It has been deeply integrated into the planning, design, construction, maintenance and management of civil infrastructures (Onat and Gul 2018, Salehi and Burgueno 2018). In the SHM community, researchers have devoted efforts to analyzing and processing the huge amount of monitoring data by the use of machine learning methods, which are key components of AI. Extracting and mining the patterns and rules inherent in the original multi-source heterogeneous field monitoring data will not only help us accurately and effectively grasp the structural service condition and the characteristics of the long-term deterioration of the target

*Corresponding author, Ph.D., Professor
E-mail: cexwye@zju.edu.cn
[a] Ph.D. Candidate
[b] Professor

http://www.techno-press.com/journals/sss&subpage=7

ISSN: 1738-1584 (Print), 1738-1991 (Online)

structure, it will also promptly issue warning information as well as make decisions regarding inspection, repair and strengthening (Min *et al*. 2015, Feng and Feng 2018).

The artificial neural network (ANN) algorithm is a classical machine learning method, and has been applied to civil engineering since 1989 (Adeli and Yeh 1989). Early ANNs were perceptrons with one or two hidden layers, and had a limited capacity for non-linearity abstraction (Wu *et al*. 1992, Szewczyk and Hajela 1994, Yun and Bahng 2000). Meanwhile, the application frameworks were realized based on the general-purpose computing languages such as FORTRAN, MATLAB or C language (Adeli 2001, Ni *et al*. 2002). Later studies employed the hand-crafted algorithms to extract features from the data and applied ANNs with a limited number of hidden layers for classification (Ceylan *et al*. 2014); while the capacity of autonomous feature learning from raw data was not available before the training of a deep neural network (DNN) (Hinton *et al*. 2006). In recent years, along with the significant improvement of network architecture and computing capacity, deep learning algorithms, e.g., convolutional neural networks (CNNs), recurrent neural networks (RNNs), etc., have experienced rapid growth, and have been applied to automatically process all kinds of data, especially image data (Dong *et al*. 2016). Many kinds of DNN frameworks and datasets have been developed to deal with various data processing scenarios and to satisfy different types of industrial demands (Vodrahalli and Bhowmik 2017).

Much research has been carried out to explore the application of deep learning-based approaches in the field of the SHM of civil infrastructures (Spencer *et al*. 2019). This paper aims to address a review on deep learning-based SHM of civil infrastructures, and is organized as follows: Section 2 briefly summarizes the history of the development of deep learning with incidents of milestones. Section 3 presents the applications of deep learning-based approaches for SHM on various kinds of civil infrastructures. Section 4 discusses the current key challenges and future trends of the deep learning-based SHM strategy. Section 5 gives some conclusions of issues dealt with in the paper.

2. A brief history of deep learning research

2.1 Significant contributions to deep learning

Nowadays, deep learning-based approaches have played an increasingly important role in the field of image recognition, natural language processing, recommendation systems, etc., to execute automated, time-saving and low-cost operations (Schmidhuber 2015, Goodfellow *et al*. 2016, Silver *et al*. 2016). Deep learning is a kind of representational learning method, which enables a network architecture to autonomously learn highly abstract features from raw data to fulfill recognition or classification tasks (Hinton and Salakhutdinov 2006, LeCun *et al*. 2015). It is a branch of machine learning, which belongs to a part of AI. Machine learning is a process of enabling a computer to learn hidden patterns among extracted features and targets for classification or prediction (Lake *et al*. 2015). Machine learning algorithms contain ANNs, support vector machines (SVMs), random forests, decision trees, Bayesian inference, etc. (Bishop 2006). AI is a system that is able to demonstrate the intelligence by machines, similar to but not the same as the natural intelligence of human beings (Russell and Norvig 2016, Silver *et al*. 2017), which contains computer vision, machine learning, robotics, speech recognition, expert systems, etc. The relationship among AI, machine learning and deep learning is shown in Fig. 1.

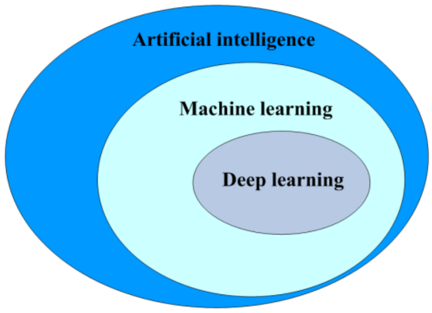

Fig. 1 Relationship of AI, machine learning & deep learning

The development of deep learning has mainly evolved from the ANN. The basic element of an ANN was called the neural cell, and has not been changed much since the first neural cell model, i.e., the MP model, was proposed in 1943 by McCulloch and Pitts (1943). A neural cell with three input elements and one output element is shown in Fig. 2. The input elements, i.e., x_1, x_2 and x_3, are multiplied by weights, i.e., w_1, w_2 and w_3, for summation, and a bias, b, is added for modification. An activation function, $f(x)$, implements nonlinear transformation to generate an output. Rosenblatt (1958) proposed a single layer perceptron structure that consisted of multiple neural cells, which could learn through perceptron convergence algorithms to improve the capacity for classification. Rumelhart *et al*. (1986) applied a back-propagation algorithm to train multi-layer neural networks, enabling the hidden layers to construct useful features for classification.

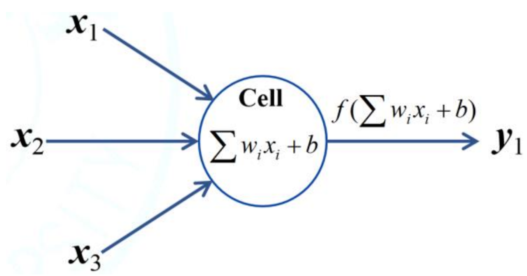

Fig. 2 The MP model (McCulloch and Pitts 1943)

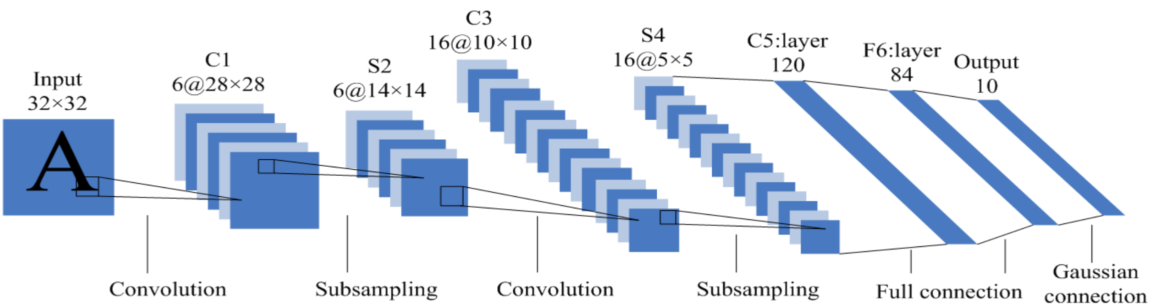

Fig. 3 The architecture of LeNet-5 (LeCun *et al.* 1998)

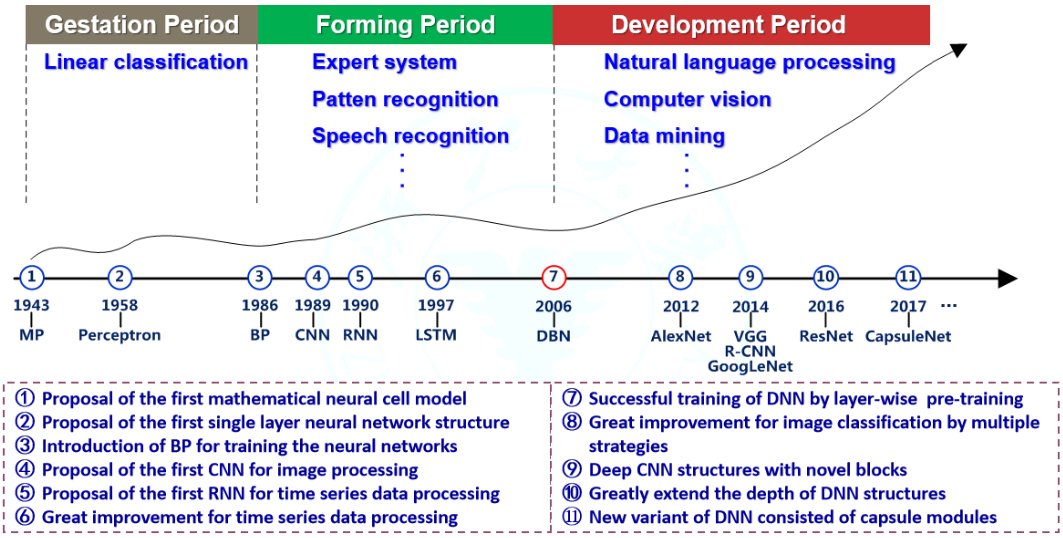

Fig. 4 Historical development of deep learning

LeCun *et al.* (1989) developed the first deep CNN, trained by a back-propagation algorithm, to recognize handwritten zip codes. Later, they proposed LeNet-5 for the recognition of handwritten characters with over 99.65% accuracy (LeCun *et al.* 1998), as shown in Fig. 3. The RNN is an important DNN for the processing of time-series data. Hopfield (1982) proposed a network with a circular structure, which was considered to be the rudiment of the RNN. Unlike the previous feed-forward neural networks, the processing of input elements in this network architecture had backward paths. Elman (1990) proposed a fully-connected RNN with local memory units and feedback connections to deal with time-series data. Hochreiter and Schmidhuber (1997) developed the long short-term memory network (LSTM) with gate units to solve the problem of long-term dependence. An LSTM cell has a forgetting gate and an input gate to filter input data, and an output gate to generate output data. However, due to the issues of gradient vanishing or explosion, it is difficult to train a DNN. This challenge prevented the development of deep learning until the deep belief network (DBN) was developed by Hinton *et al.* (2006). They trained the DBN by unsupervised greedy training for each layer and then fine-tuning by a supervised back-propagation algorithm.

Furthermore, the training of a DNN requires the processing of a massive amount of data with the help of a great computing power. The improvement of the efficiency of training is critical to the practical application of a DNN. To accelerate the training process, Chellapilla *et al.* (2006) proposed a graphics processing unit (GPU)-accelerated convolutional network and produced a 3.1X-4.1X speedup. Raina *et al.* (2009) constructed a GPU-aided deep unsupervised learning network which was simple to program and needed less time for training. Ciresan *et al.* (2010) presented a GPU-accelerated approach to efficiently train the multi-layer perceptron (MLP). With the progress of GPU-based training methods, the efficiency of training a DNN has been drastically improved. However, when the neural networks become deeper, the number of parameters grows explosively and this generates the problem of overfitting.

Krizhevsky *et al.* (2012) won the 2012 ImageNet challenge by the proposal of AlexNet with proper treatment of the overfitting issue. To reduce the overfitting effect, relu, dropout, and data augmentation were jointly adopted to train the network architecture with about 60 million parameters. Also, two GPUs were applied to speed up the training process of the CNN. The joint application of these techniques enabled AlexNet to obtain a 15.3% top-5 error rate in the image classification for 1000 different categories.

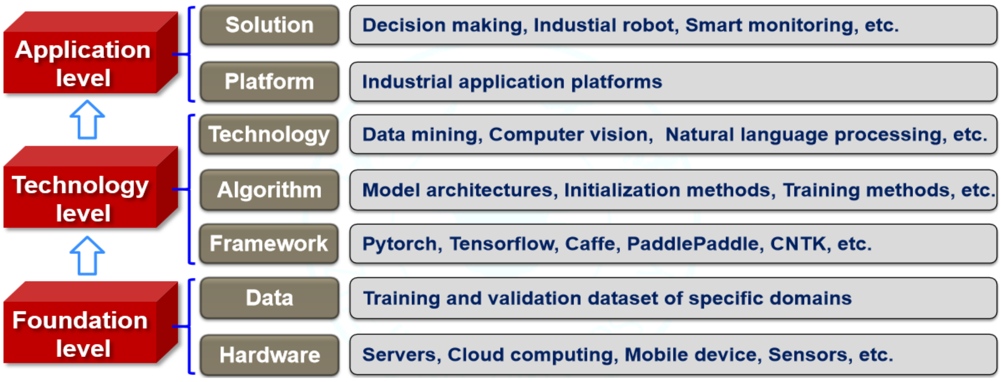

Fig. 5 Industrial chain of deep learning

The milestone success of AlexNet shocked scholars and engineers all over the world and attracted more attention to the research on deep learning. Up to now, a lot of DNNs have been proposed for many kinds of application purposes. CapsuleNet is able to recognize and reconstruct target objects in images (Hinton *et al*. 2011, Sabour *et al*. 2017). VGG-Net (Simonyan and Zisserman 2014), ZF-Net (Zeiler and Fergus 2014), GoogLeNet (Szegedy *et al*. 2014) and ResNet (He *et al*. 2016) are good at classification. U-Net (Ronneberger *et al*. 2015), DeconvNet (Noh *et al*. 2015), CRF-RNN (Zheng *et al*. 2015), ENet (Paszke *et al*. 2016), PSPNet (Zhao *et al*. 2017), RefineNet (Lin *et al*. 2017), fully convolutional network (FCN) (Shelhamer *et al*. 2017), DenseNet (Huang *et al*. 2017) and Deeplab (Chen *et al*. 2018) are suitable for segmentation tasks. R-CNN (Girshick *et al*. 2014, Ren *et al*. 2015), MobileNet (Howard *et al*. 2017), SegNet (Badrinarayanan *et al*. 2017) and ShuffleNet (Zhang *et al*. 2018) are fit for target detection tasks. GAN (Goodfellow *et al*. 2014), *f*-GAN (Nowozin *et al*. 2016), EBGAN (Zhao *et al*. 2016) and InfoGAN (Chen *et al*. 2016) could be utilized for imaginary processing of images, videos, etc. More studies can be found in LeCun *et al*. (2015). The historical development of deep learning is illustrated in Fig. 4.

2.2 Frameworks and datasets for deep learning

Deep learning frameworks are crucial tools for the application of deep learning-based approaches and have been developed by many companies and research institutes. Caffe was proposed by the University of California, Berkeley in 2013, and it supports CNN well. The explanations, demos and related papers can be found at http://caffe.berkeleyvision.org/. Tensorflow is an open source software developed by Google in 2015, which can connect well with python and C++. The detailed resource can be found at https://tensorflow.google.cn/. PyTorch was developed by Facebook in 2016, and it supports a dynamic computation graph. Examples and tutorials are available at https://github.com/pytorch. Besides the above-mentioned popular frameworks, there are other frameworks. MXNet was developed by Amazon in 2015, and is available at http://mxnet.incubator.apache.org/. CNTK was developed by Microsoft in 2016, available at https://archive.codeplex.com/?p=cntk. PaddlePaddle was developed by Baidu in 2016, available at https://www.paddlepaddle.org.cn/.

The demand for tremendous training data is a big challenge in the training process. To sufficiently train DNNs for different tasks, the number of training samples is counted by tens of thousands. Thus, a variety of datasets were established to support the training demand. MNIST is a dataset of handwritten digits containing 60000 training images and 10000 testing images, available at https://datahack.analyticsvidhya.com/contest/practice-problem-identify-the-digits/#data_dictionary. MS-COCO is a dataset for object detection and segmentation, available at http://cocodataset.org/#people. WordNet is a large lexical dataset of English, containing words of nouns, verbs, adjectives and adverbs, available at https://wordnet.princeton.edu/. ImageNet is a dataset of images built based on WordNet to provide the graphical explanation of each word in the form of synonym sets, available at http://www.image-net.org/. Open images dataset contains millions of images covering thousands of classifications with labeled bounding boxes, available at https://github.com/openimages/dataset. Wikipedia Corpus contains words from over 4 million articles and is a powerful natural language processing dataset, available at https://nlp.cs.nyu.edu/wikipedia-data/. More datasets of different categories can be found at https://www.analyticsvidhya.com/blog/2018/03/comprehensive-collection-deep-learning-datasets/. The industrial chain of deep learning is illustrated in Fig. 5.

3. Applications of deep learning in the SHM of civil infrastructures

Researchers and engineers in the field of civil engineering have already noticed the fantastic prospects and innovative technological strength brought about by deep learning-based approaches (DeVries *et al*. 2018, Spencer *et al*. 2019). Many kinds of attempts have been made to apply deep learning-based approaches to the SHM of civil infrastructures (Vodrahalli and Bhowmik 2017). In this section, the research work has been collected and mainly classified into two categories: structural damage detection and structural condition assessment.

Table 1 Applications of deep learning-based structural damage detection

Structure type	Application	Reference	Technology
Bridge	Crack detection	Alipour *et al*. (2019)	FCN
		Dung *et al*. (2019)	VGG-16+Transfer learning
		Kim *et al*. (2018)	UAV+R-CNN+Transfer learning+IPT
		Sajedi and Liang (2019)	SegNet
	Damage detection	Bao *et al*. (2019)	Auto-encoder+Unsupervised learning
		Duan *et al*. (2019)	CNN
		Liang (2019)	VGG-16+Faster R-CNN+SegNet
		Tang *et al*. (2019)	CNN
		Yeum *et al*. (2019)	CNN+UAV+Structure from motion
	Loosened bolt detection	Huynh *et al*. (2019)	R-CNN
	Damage state classification	Khodabandehlou *et al*. (2019)	CNN
Tunnel	Crack detection	Li *et al*. (2019)	Faster R-CNN
		Song *et al*. (2019)	ResNet+MobileNet+CrossNet
	Multiple damage detection	Huang *et al*. (2018)	FCN
		Gao *et al*. (2019)	Faster R-CNN+FCN
		Xue and Li (2018)	FCN+Faster R-CNN
Highway	Crack detection	Bang *et al*. (2019)	Encoder-decoder network
		Gopalakrishnan *et al*. (2017)	VGG-16+Transfer learning
		Hoang *et al*. (2018)	CNN
		Maeda *et al*. (2018)	MobileNet+Inception
		Park *et al*. (2019)	FCN+CNN
		Tong *et al*. (2017)	CNN
		Tong *et al*. (2018)	CNN+Transfer learning
		Zhang *et al*. (2017)	CNN without pooling
		Zhang *et al*. (2018)	Light weight CNN
		Zhang *et al*. (2018)	AlexNet+Transfer learning
		Zhang *et al*. (2019)	RNN
Railway	Fastener damage detection	Liu *et al*. (2019)	CNN
		Wei *et al*. (2019)	VGG-16+Faster R-CNN
	Insulator damage detection	Kang *et al*. (2019)	Faster R-CNN
	Multiple damage detection	Gibert *et al*. (2017)	CNN
Concrete building	Crack detection	Cha *et al*. (2017)	CNN
		Dorafshan *et al*. (2018)	AlexNet+Transfer learning
		Dung and Anh (2019)	FCN+Transfer learning
		Kang and Cha (2018)	UAV+CNN
		Kim and Cho (2018)	UAV+AlexNet+Transfer learning
		Kim and Cho (2019)	Mask R-CNN
		Ni *et al*. (2019)	GoogLeNet+ResNet
		Ni *et al*. (2019)	GoogleNet+Transfer learning
		Yang *et al*. (2018)	VGG-19+FCN
		Ye *et al*. (2019)	FCN
		Zhang *et al*. (2019)	SegNet
		Zhang *et al*. (2019)	ResNet+FCN
	Multiple damage detection	Gao and Mosalam (2018)	VGG+Transfer learning
		Li *et al*. (2018)	Faster R-CNN
		Li *et al*. (2019)	DenseNet+FCN
		Lin *et al*. (2017)	CNN
		Wang *et al*. (2018)	AlexNet+GoogLeNet
		Xu *et al*. (2019)	Faster R-CNN
		Yeum *et al*. (2018)	AlexNet
	Spalling detection	Beckman *et al*. (2019)	Faster R-CNN
	Damage dataset generation	Gao *et al*. (2019)	GAN
Steel building	Damage detection	Gulgec *et al*. (2019)	CNN
		Liu and Zhang (2019)	CNN
		Pathirage *et al*. (2018)	Auto-encoder
		Yu *et al*. (2019)	CNN
		Zhao *et al*. (2019)	VGG-16+MobileNet
	Multiple damage detection	Chen and Jahanshahi (2018)	CNN+Naive Bayes
		Wu *et al*. (2019)	VGG-16+ResNet-18
	Stiffness degradation detection	Zhou *et al*. (2019)	Auto-encoder
	Joint damage detection	Abdeljaber *et al*. (2017)	1D-CNN
	Corrosion detection	Atha and Jahanshahi (2018)	CNN
	Crack detection	Cha *et al*. (2018)	Faster R-CNN
Pipe	Defect detection	Cheng and Wang (2018)	Faster R-CNN
		Kumar *et al*. (2018)	CNN
		Li *et al*. (2019)	ResNet
		Wang and Cheng (2019)	CNN+FCN

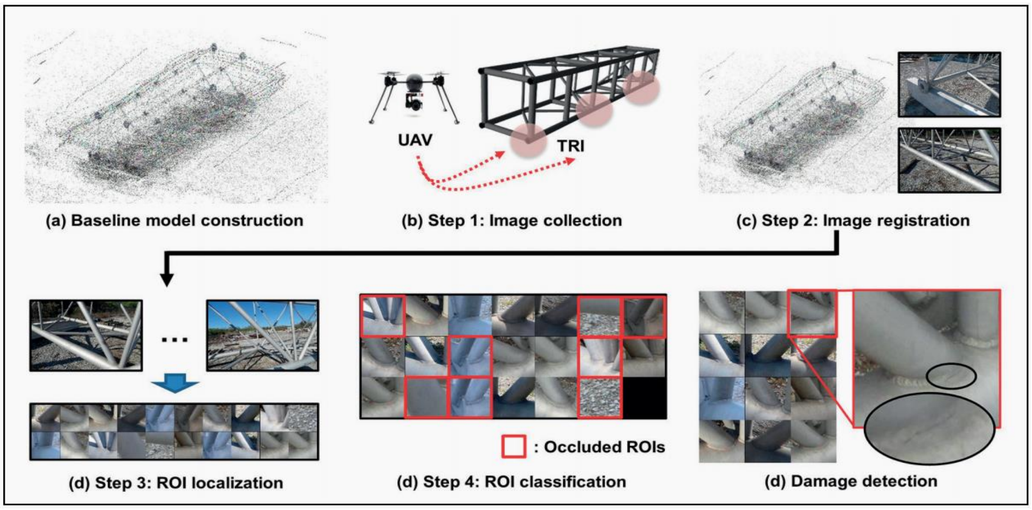

Fig. 6 UAV and CNN-based weld line damage detection (Yeum *et al*. 2019)

3.1 Structural damage detection

Structural damage inspection is essential for the safety of in-service structures, and thus many research groups have utilized the deep learning-based approaches to carry out damage detection on a variety of structures. Applications of deep learning-based studies are collected and listed in Table 1. There have been numerous image-based and CNN-based studies as many kinds of structural damages are visible. To overcome the lack of annotated image datasets for specific inspection purposes, transfer learning was implemented by pre-training with a large number of open-source image datasets and fine-tuning with a small number of collected images. Also, conventional data augmentation techniques as well as deep learning-based approaches such as GAN were used to enlarge the datasets. To detect, localize and quantify the structural damages such as spalling and cracks, the Faster R-CNN and FCN approaches were adopted to precisely locate the damages and the image processing techniques (IPTs) were applied to obtain the damage parameters. Addition to the images, the time-series data such as acceleration and displacement were used for damage detection in those studies. To process the time-series data, the auto-encoder networks and 1D-CNN were developed by several research groups. Besides, transforming the raw time-series data into the frequency spectra or spatial time-frequency spectra for further processing was also being investigated.

3.1.1 Bridges

Kim *et al*. (2018) proposed a UAV and R-CNN-based approach to detect cracks in the aged concrete bridges. A pre-trained R-CNN was fine-tuned by crack images for crack detection, and the IPTs were adopted to quantify the detected cracks. Liang (2019) proposed a three-level deep learning-based method for the inspection of post-disaster bridges. VGG-16 was applied to detect system-level failure, and Faster R-CNN and SegNet were adopted to detect component-level and local-level damage respectively. Sajedi and Liang (2019) developed a semantic segmentation neural network based on SegNet to automatically localize cracks. The performance of different training algorithms, i.e., stochastic gradient descent (SGD), RMSprop, Adagrad, Adadelta, Adam, and Adamax, were compared by precision rate and recall rate. Yeum *et al*. (2019) developed an automatic and robust technique for the localization and classification of the region of interest (ROI) for the vision-based weld line assessment, as shown in Fig. 6. A 3D geometric relationship between the targeted region and the images was generated by utilizing a structure from motion algorithm. The most useful ROI was obtained by using a CNN acting as a binary occlusion classifier. Khodabandehlou *et al*. (2019) established an eleven-layer CNN to conduct damage state classification. Acceleration data from shaking table tests of a reinforced concrete bridge model under different loads were utilized for validation. Bao *et al*. (2019) developed an auto-encoder-based network to detect data anomalies. The proposed network was trained by unsupervised pre-training and supervised fine-tuning. Acceleration data from a cable-stayed bridge was used for validation, and six kinds of data anomalies were detected with a global accuracy of 87%.

Dung *et al*. (2019) compared three deep learning-based methods based on transfer learning to detect the cracks at the welded joints of gusset plates. A shallow CNN trained from scratch, a pre-trained VGG-16 with a fine-tuned classifier, and a pre-trained VGG-16 with a fine-tuned convolution layer and classifier were compared by use of accuracy rate, precision rate, and recall rate. Raw images from experiments and daily inspections were collected for the establishment of the dataset, and data augmentation was adopted to reduce overfitting. Huynh *et al*. (2019) proposed an R-CNN and Hough line transform-based approach to detect the loosened bolts of steel connections. A 15-layer R-CNN was pre-trained without bolt images and fine-tuned with bolt images. The Hough line transform algorithm was adopted to assess the condition of the loosening of the detected bolts. Alipour *et al*. (2019) proposed an FCN-based

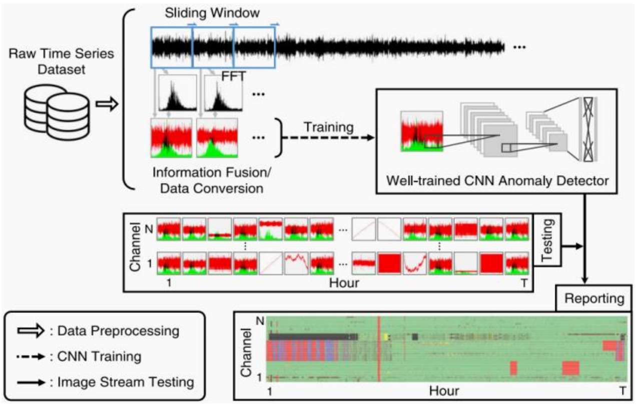

Fig. 7 CNN-based anomaly detection of time series data (Tang *et al.* 2019)

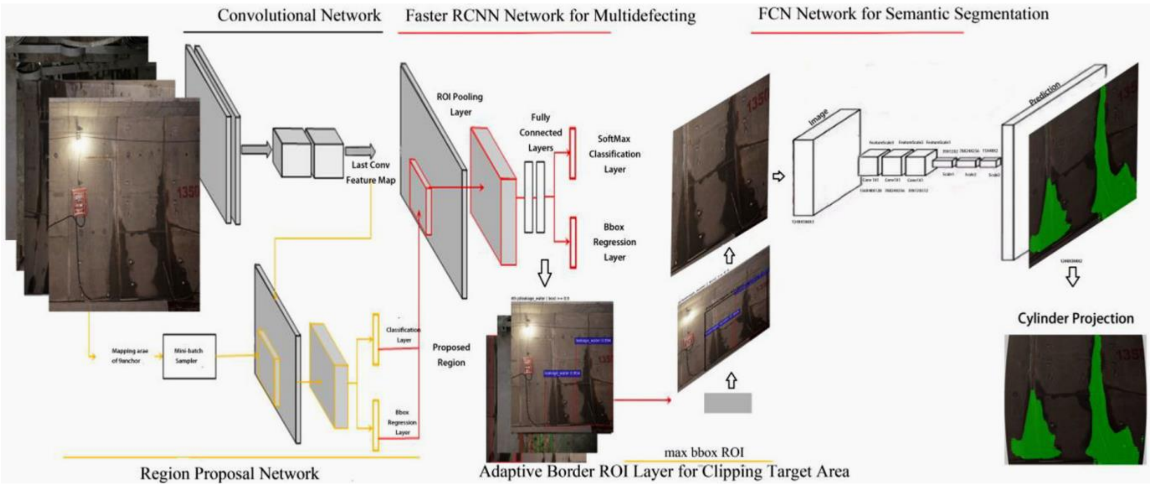

Fig. 8 FCN and R-CNN-based tunnel crack detection (Gao *et al*. 2019)

approach to detect cracks for refined crack assessment. Five models with different upsampling rates were tested based on the pre-trained state. The image dataset was established by the collected on-site crack images with careful annotation, and the influence of the size of the dataset was analyzed. Duan *et al*. (2019) proposed a CNN-based approach to detect bridge damages by acceleration responses. Numerical analysis of a tied-arch bridge with different damage conditions was conducted to generate acceleration responses. The acceleration responses and generated Fourier spectra were used as datasets, and the performances of damage detection were compared. Tang *et al.* (2019) designed a five-layer CNN to detect and classify anomalous monitoring data from an SHM system, as shown in Fig. 7. Acceleration data from a cable-stayed bridge was utilized and divided into training sets with different sizes for performance evaluation.

3.1.2 Tunnels

Xue and Li (2018) developed a three-stage deep learning-based framework for the classification and localization of tunnel lining damages. An FCN was developed to extract feature maps of input images, a region proposal network was applied to select suspicious regions on the feature maps, and a position-sensitive pooling method was applied to precisely locate damages. Huang *et al.* (2018) employed an FCN-based two-stream approach to implement semantic segmentation for cracks and leakages in tunnels. Comparison of performance was conducted among the proposed approach, a region growing algorithm, and an adaptive thresholding algorithm. Song *et al.* (2019) compared the performance of three different kinds of DNNs for semantic segmentation of tunnel cracks. To train the tested networks, tunnel images of real-world situations were collected and a tunnel crack dataset with semantic segmentation annotation was established. Gao *et al*. (2019) established a Faster R-CNN and FCN-based framework for quick and accurate detection of multiple tunnel defects, as shown in Fig. 8. A Faster R-CNN was used to select defect images, and then an adaptive border boundary module was employed to reduce the size of the selected images. Finally, an FCN was applied to detect defects in the pixel-wise level. Li *et al*. (2019) proposed an image processing and Faster R-CNN-based framework to detect tunnel cracks. A dataset containing three crack types was built to train the Faster R-CNN.

3.1.3 Highways

Gopalakrishnan *et al*. (2017) developed a pre-trained VGG-16-based method to detect pavement cracks. The pre-training of the VGG-16 was based on the pavement dataset of ImageNet, and the complexity of recognition was introduced by a mixture of hot-mix asphalt pavement and concrete pavement images. Tong *et al*. (2017) combined three CNNs for recognition, location, and feature extraction operations to implement the 3D reconstruction of concealed pavement cracks. Images of cracks underneath the asphalt pavement were obtained by a ground penetrating radar. Zhang *et al.* (2017) proposed a CNN model called CrackNet to automatically detect pavement cracks on 3D images of asphalt road surfaces. The proposed CrackNet had no pooling layers to keep the size of feature maps for pixel-wise detection of cracks.

Zhang *et al*. (2018) proposed a modified model of CrackNet called CrackNet II for crack identification with greater precision and better recall rates. In comparison with CrackNet, the modified version had a deeper architecture with fewer parameters and a better degree of computing efficiency. Tong *et al*. (2018) proposed a two-stage CNN-based approach for the automatic measurement of the length of pavement cracks. The proposed CNN was pre-trained by images with crack labels, and fine-tuned by images with detailed labels of the length of cracks. The *k*-means clustering analysis was adopted to preprocess raw crack images for the establishment of a crack dataset. Hoang *et al.* (2018) compared two edge detection methods and a CNN-based approach for the recognition of pavement cracks. The Sobel and Canny detection methods were applied with a thresholding optimization method to enhance the robustness of crack detection, and a 7-layer CNN was trained to detect cracks for comparison. Zhang *et al*. (2018) proposed an AlexNet and IPT-based framework to detect the pavement cracks in a real-world situation. A pre-trained and fine-tuned AlexNet was adopted to detect crack regions from the captured raw images. Maeda *et al*. (2018) applied MobileNet and Inception to detect multiple road damages. A large dataset containing plenty of images obtained by on-board smartphones was established to provide sufficient training and validation images. The accuracy and time of computation were compared in order to evaluate the performance.

Zhang *et al.* (2019) proposed an RNN-based model called CrackNet-R to detect pavement cracks in 3D images in pixel-level. To improve the capacity of feature extraction, a recurrent unit and gated recurrent multi-layer perceptron were proposed to implement the nonlinear transformation on gating units. Bang *et al*. (2019) proposed an encoder-decoder network for the detection and localization of road cracks in video frames obtained by on-board cameras. For the extraction performance of the encoder architecture, a comparative study was conducted to select the best architecture from VGG-16, ResNet-152, ResNet-200, ResNet-101 and ResNet-50. Park *et al*. (2019) proposed an FCN and CNN-based framework to implement pavement crack identification. An FCN was adopted to select the road images with the presence of disturbing objects such as vehicles, pedestrians, plants, etc. A CNN was applied to detect cracks in the selected images.

3.1.4 Railways

Gibert *et al*. (2017) proposed a CNN-based framework to detect multiple railway damages. The framework shared three convolutional layers for material classification, fastener classification, and fastener damage detection. Kang *et a*l. (2019) developed a two-step framework to detect insulator damage. A Faster R-CNN was applied to grab component images containing insulators, and a deep multi-task neural network was applied to evaluate the conditions of the insulator. Liu *et al*. (2019) proposed a similarity-based CNN for the inspection of the conditions of fasteners. The similarity of pairs of fastener images was calculated to assess the capacity of feature extraction in the pre-training stage. To enlarge the training dataset, a template matching-based classification approach was adopted to select large numbers of fastener images from online railway images. Wei *et al*. (2019) compared the performance of the capacity for the detection of defects for the fasteners among IPTs, VGG-16 and Faster R-CNN. The Faster R-CNN achieved the best performance evaluated by precision rate and recall rate.

3.1.5 Concrete buildings

Cha *et al*. (2017) proposed a CNN-based method for the detection of structural cracks. Testing images contained cracks with different widths, lighting conditions, and noise levels. The Sobel and Canny detection methods were adopted for the comparison of the capacity for detection. Lin *et al.* (2017) proposed a CNN-based method to automatically extract features from time domain data for damage detection. A wavelet-based method was adopted for comparison of detection performance. Yeum *et al*. (2018) proposed an AlexNet-based two-stage framework for collapse classification and spalling detection in post-event analysis for concrete buildings. A dataset for post-event reconnaissance images was built by collecting a large number of images after natural disasters including hurricanes, tornadoes, and seismic incidents. Li *et al*. (2018) proposed a Faster R-CNN-based framework to detect and localize multiple defects in different scenarios. To strengthen the capacity for detection of multiple defects, the multi-scale training, data augmentation and negative mining strategies were jointly adopted. For the localization of defects, a location block was introduced and improved in the framework. Kang and Cha (2018) proposed an automatic unmanned aerial vehicle (UAV) and CNN-based damage detection approach for application in indoor environments. The geo-tagging method based on stationary beacons was applied to navigate the UAV and locate the damage. Dorafshan *et al*. (2018) conducted a comparison between edge detection methods and AlexNet for the detection of concrete cracks. Edge detection algorithms contained Roberts, Prewitt, Sobel and LoG algorithms in the spatial domain, and Butterworth and Gaussian algorithms in the frequency domain. The performance of AlexNet was compared in a transfer learning mode and a fully trained mode. Gao and Mosalam (2018) proposed a VGG-based architecture to detect damage to structural components, as shown in Fig. 9. Transfer learning was adopted to obtain a robust recognition performance with a

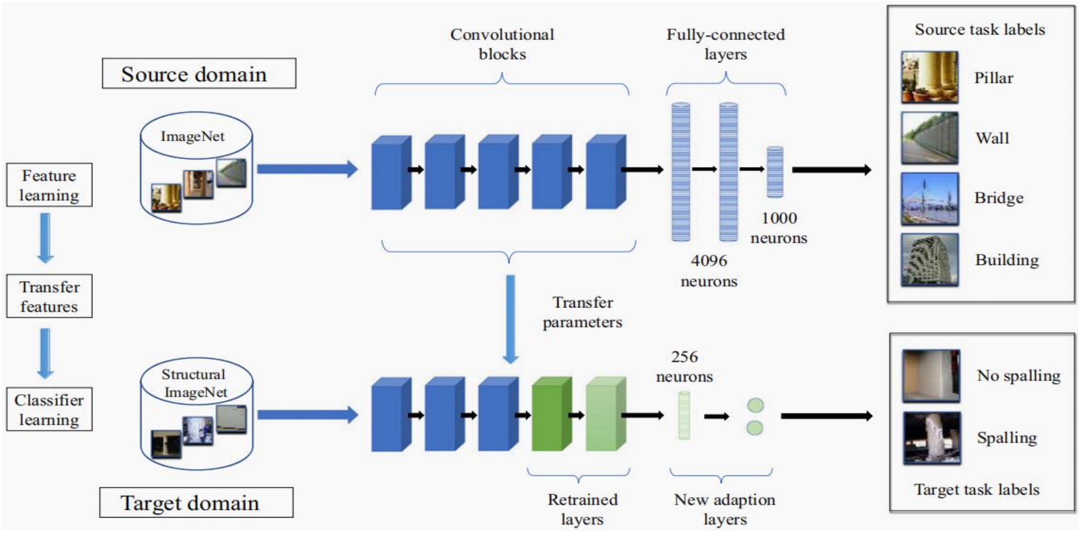

Fig. 9 Transfer learning-based multiple damage detection (Gao and Mosalam 2018)

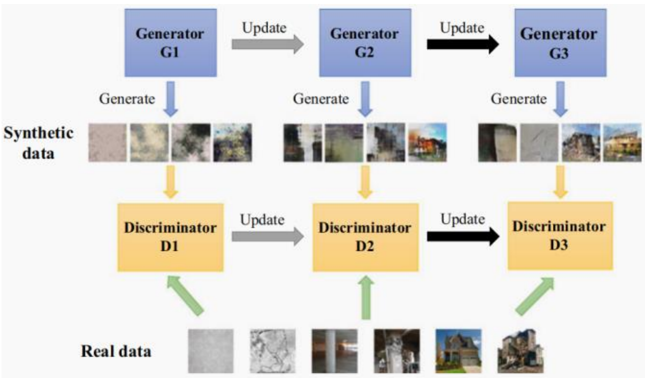

Fig. 10 GAN-based dataset generation (Gao *et al.* 2019)

small training dataset. An image dataset called Structural ImageNet was built to collect images for the training process. Yang *et al.* (2018) proposed a VGG-19 based FCN to detect cracks in different scales. Segmented crack pixels were processed to a single pixel width skeleton for post evaluation of morphological features including crack topology and length, etc. Kim and Cho (2018) proposed a method consisting of a probability map and an AlexNet trained by online images to detect cracks. On-site images and video frames taken by a UAV were collected for testing. The average precision rate and recall rate for image-based crack detection were about 10% higher than those for video frame-based crack detection. Wang *et al.* (2018) applied AlexNet and GoogLeNet to detect multiple damages to masonry walls, and the sliding window techniques were used to locate the damages. A comparative study was conducted by the use of the image datasets with different sizes.

Zhang *et al.* (2019) proposed a residual block-based FCN with dilated convolution to detect concrete cracks. Residual blocks were used to extract features and dilated convolutions were conducted with different dilation rates for different receptive fields. Dung and Anh (2019) proposed an FCN-based method for the detection of cracks on concrete surfaces. A VGG-16-based model, an InceptionV3-based model, and a ResNet-based model were compared for feature extraction performances to select the best encoder for the proposed FCN. Ni *et al.* (2019) proposed a GoogLeNet and ResNet-based method for the detection of cracks. Zernike moment operator was used to process crack images detected by the proposed method for the quantification of thin cracks. Li *et al.* (2019) proposed a DenseNet-121-based FCN to detect the concrete defects including spalling, cracks, efflorescence and holes. Model-based transfer learning was adopted to assign the initial parameters of the FCN in the training procedure. Zhang *et al.* (2019) proposed a SegNet-based model with context awareness to detect cracks in images of arbitrary sizes. A context-aware fusion algorithm was developed to merge the detected crack image patches generated by a sliding window technique. Datasets including the CrackForest dataset, the Management dataset, the Tomorrows Road Infrastructure Monitoring dataset, and the Customized Field Test dataset were tested for the validation of the proposed model. Ni *et al.* (2019) proposed a CNN-based two-stage method to detect structural cracks. Pre-trained and fine-tuned GoogleNet was utilized to detect cracks, and a crack delineation network was adopted to conduct feature map

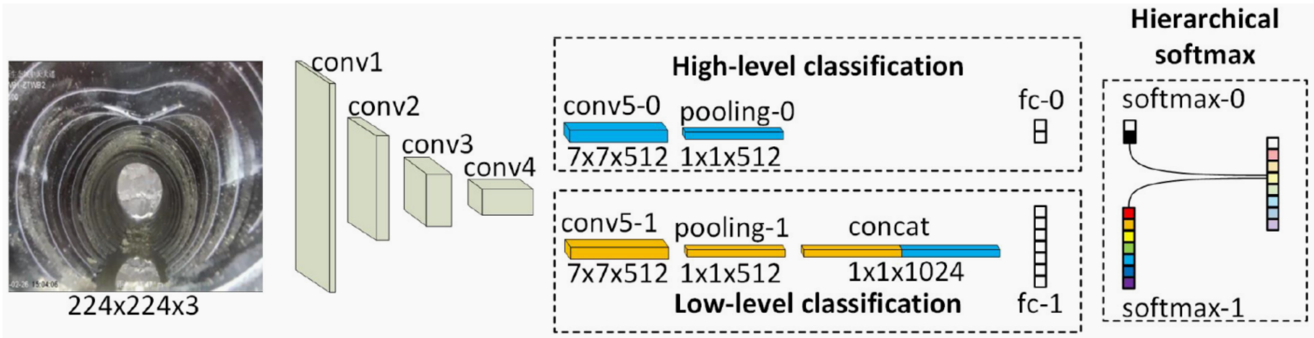

Fig. 11 ResNet-based sewer defect detection (Li *et al*. 2019)

Table 2 Applications of deep learning-based structural condition assessment

Structure type	Application	Reference	Technology
Bridge	Serviceability analysis	Liang *et al*. (2016)	CNN+RNN
	Rebar assessment	Dinh *et al*. (2018)	CNN+IPT
Pavement	Texture depth assessment	Tong *et al*. (2018)	CNN
	Friction assessment	Yang *et al*. (2018)	CNN
Bridge	Data reconstruction	Fan *et al*. (2019)	FCN
	Modal analysis	Kim and Sim (2019)	Faster R-CNN
	Ship detection	Li *et al*. (2019)	VGG-16+Transfer learning+IPT
	Spectrum analysis	Liu *et al*. (2019)	LSTM
	Condition assessment	Zhang *et al*. (2019)	1D-CNN
	Vehicle load analysis	Zhang *et al*. (2019)	Faster R-CNN
Railway	Condition assessment	Wang *et al*. (2019)	ResNet+DenseNet
Truss	Deformation assessment	Lee *et al*. (2018)	MLP
Building	Condition assessment	Rafiei and Adeli (2018)	Encoder-decoder network
	Dynamic response estimation	Oh *et al*. (2019)	CNN
Electric tower	Condition assessment	Dick *et al*. (2019)	CNN
Steel frame	Dynamic response estimation	Wu and Jahanshahi (2019)	CNN
Offshore platform	Load prediction	Lyu *et al*. (2019)	DBN

fusion for the delineation of pixel-wise cracks. Xu *et al*. (2019) proposed a Faster R-CNN based model to detect and localize multiple types of seismic damages such as cracks and spalling. A region proposal network was merged into a Fast R-CNN by sharing preliminary feature maps. The image dataset was established by on-site picturing and data augmentation was adopted to enlarge the dataset. Kim and Cho (2019) proposed a Mask R-CNN-based framework for the detection and quantification of concrete cracks. The training images of concrete cracks were collected from an on-site concrete wall and it contained cracks with different widths. Ye *et al*. (2019) developed a U-Net-based FCN to automatically detect cracks on concrete surfaces. An online dataset of crack images with pixel-wise labels was collected for training and validation. Gao *et al*. (2019) proposed a GAN-based architecture to generate concrete structural damage images for the establishment of a training dataset, as shown in Fig. 10. A leaf-bootstrapping method was adopted to improve the capacity for generation of the proposed model. The generated synthetic images were evaluated by a self-inception score and indices of the generalization ability. Beckman *et al*. (2019) proposed a Faster R-CNN and depth camera-based approach to detect and quantify the spalling of structural components. The Faster R-CNN was trained by on-site spalling images and applied to detect the spalling areas in images, and the depth of the spalling was measured by a depth camera for the volumetric evaluation of the detected spalling.

3.1.6 Steel buildings

Abdeljaber *et al*. (2017) developed a one-dimensional CNN for vibration-based structural damage detection of a steel structure with acceleration data. Atha and Jahanshahi (2018) proposed two CNN-based architectures called Corrosion-5 and Corrosion-7 to detect corrosion on metallic surfaces. The performance of the proposed architectures was compared with ZF Net, VGG-15, and VGG-16 by the precision rate, recall rate and F1 score. Chen and Jahanshahi (2018) combined a CNN-based approach with a Naive Bayes data fusion method to detect the cracks in video frames of nuclear power plants. A CNN was applied for the detection of cracks in each video frame, and a naive Bayes decision-making scheme was used to eliminate non-crack patches. Cha *et al*. (2018) proposed a Faster R-CNN-based method for the structural visual inspection of defects including concrete cracks, bolt corrosion, steel corrosion, and steel delamination. Pathirage *et al*. (2018) proposed an auto-encoder-based architecture to identify structural damage by vibration responses. Numerical and experimental studies were conducted to generate datasets for the training, validation and testing of the proposed architecture.

Gulgec *et al*. (2019) proposed a CNN-based approach to classify damaged and undamaged steel structure components generated by numerical simulations. To select a feature extractor, 50 CNNs with different learning rates, convolutional and fully-connected layers were trained and compared. To build a localization detector, a similar comparative study was conducted based on 70 settings. Liu and Zhang (2019) developed a CNN-based method for the assessment of damage conditions for the post-hazard evaluation of structural steel fuse members. Images of cumulative plastic strain contours generated by numerical analysis and experimental study were adopted for the training and validation of the proposed method. Zhou *et al*. (2019) trained an auto-encoder-based network by histogram of stiffness to implement damage identification via stiffness deterioration. A training dataset of the histogram of stiffness including typical linear and nonlinear structural behavior was obtained by analysis of simulated random hysteresis loops. Yu *et al*. (2019) proposed a deep CNN-based framework to recognize the damage of a smart steel structure with isolators. The training dataset was generated by the numerical simulation of the steel structure models. Wu *et al*. (2019) proposed a DNN and pruning algorithm based method to detect structural damages. VGG-16 and ResNet-18 were trained by a high performance server, and the damage dataset contained crack and corrosion images that were carefully collected from field infrastructures. Zhao *et al*. (2019) proposed a VGG-16-based method to detect the condition of bolt loosening for steel structures. After training, validation and testing, a MobileNet was utilized to implement the detection process with a smartphone.

3.1.7 Pipes

Cheng and Wang (2018) established a Faster R-CNN-based approach to detect defects in sewer pipes. Training was conducted with images collected from closed-circuit television inspection. Six models with different parameters were compared, and indices including training time, accuracy and detection speed were adopted for performance evaluation. Kumar *et al*. (2018) developed a CNN-based system to detect and classify defects including deposits, root intrusions, and cracks. Training was conducted with 12000 images collected from in-situ inspection of 200 pipes. Wang and Cheng (2019) proposed an integrated architecture called DilaSeg-CRF to improve the accuracy of segmentation for the detection of defects in sewer pipes. DilaSeg-CRF combined a deep CNN with dense conditional random fields, and adopted a multi-scale convolution strategy to address the segmentation of the defects with different scales. FCN, DilaSeg-Basic and DilaSeg were compared by the IoU index. Li *et al*. (2019) proposed a two-level ResNet-based approach for sewer defect detection with consideration of imbalanced distribution of the dataset, as shown in Fig. 11. The high-level framework was used to select images with defects, and the low-level framework was used to detect specific defects.

3.2 Structural condition assessment

Structural condition assessment is helpful for obtaining the structural state for maintenance, and for revealing the long-term evolutionary law of structural service behavior. Investigations of deep learning-based structural condition assessment are collected and listed in Table 2. The image-based structural condition assessment was conducted by use of CNN-based approaches. As for the processing of time-series data, 1D-CNN and LSTM were utilized to deal with the time-dependent issue. Applications of deep learning-based structural condition assessment are mainly divided into two categories: transportation infrastructure and buildings.

3.2.1 Transportation infrastructures

Liang *et al*. (2016) established a multi-scale SHM system to assess the serviceability of the bridge based on a Hadoop Ecosystem. To implement the analysis of component-level reliability, images were processed by a CNN, and streaming data were processed by an RNN. Yang *et al*. (2018) proposed a CNN model called FrictionNet for pavement skid resistance and safety analysis by pavement texture data. High-speed texture profiles and grip tester friction data were collected for training and validation. Dinh *et al*. (2018) proposed a two-stage framework based on IPT and CNN to detect and localize the rebars in the ground penetrating radar images. The image migration and thresholding method was adopted to select the potential rebar images and a 14-layer CNN was adopted to detect the rebars. Tong *et al*. (2018) proposed a CNN-based approach to analyze the depth of the texture of the surface of the pavement by use of the 3D on-site scanning images. IPTs were used to verify the robustness of the proposed approach.

Wang *et al*. (2019) proposed a dual path network consisting of ResNet and DenseNet to classify different railway events by monitoring data containing environmental noise. A dataset of a spatial time-frequency spectrum was established by multi-dimensional vibration signals. An on-site railway safety monitoring test was conducted to validate the proposed method. Zhang *et al*. (2019) proposed a Faster R-CNN-based framework to track multiple vehicles on bridges to evaluate the load condition, as shown in Fig. 12. Based on the detection results, image calibration was adopted to obtain vehicle parameters including vehicle length, speed, detailed lanes, etc. Eight types of vehicle images were selected as the dataset.

Zhang *et al*. (2019) proposed a one-dimensional CNN-based approach to assess the structural state by acceleration signals. A dataset for training, validation and testing was established from an indoor test of a bridge model, an outdoor test of a full-scale bridge model, and a test of an in-service bridge. Kim and Sim (2019) proposed a deep

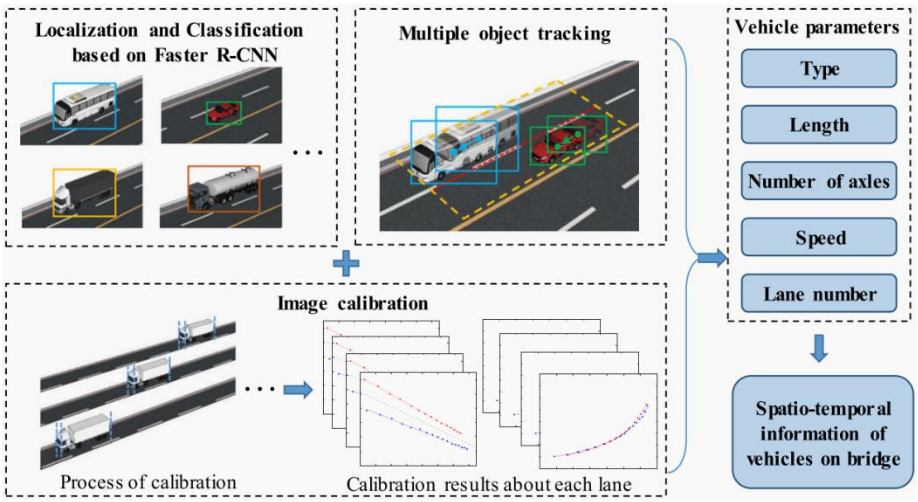

Fig. 12 Faster R-CNN-based vehicle detection (Zhang *et al.* 2019)

learning-based framework consisting of a Fast R-CNN and a region proposal network for the automated peak picking in the mode identification in frequency domain. An acceleration dataset was established from the model experiments of a simply supported beam and a simply supported truss, and the on-site test of a cable-stayed bridge. Fan *et al*. (2019) proposed an FCN-based architecture to reconstruct incomplete acceleration data of a pedestrian bridge monitored by wireless sensors. The training dataset was obtained from a long-term SHM system, and the testing dataset was generated by the processing of original data with different loss ratios. The reconstructed data was compared with the original one in the time and frequency domain for the performance evaluation of the proposed architecture. Li *et al*. (2019) proposed a modified VGG-16 and IPT-based framework to detect multiple parameters of ships coming towards bridges to prevent collision incidents. The modified VGG-16 network was pre-trained and fine-tuned by the online ship images to coarsely detect and localize the incoming ships. IPTs were applied to calculate the ship parameters including width, length, velocity, etc. Liu *et al*. (2019) proposed a video frame and LSTM-based approach to measure the vibration frequency of multiple structures. The indoor beam test and in-service bridge test were conducted to validate the proposed method, and accelerometers were used to perform a frequency analysis in the conventional way for the comparison of performance.

3.2.2 Buildings

Rafiei and Adeli (2018) presented an unsupervised learning-based framework for the assessment of local and global conditions of structural systems via collected vibration response data. The effectiveness of the proposed method was verified by experimental data from a shaking table test. Lee *et al*. (2018) compared DNN architectures with different hidden layers, activation functions, and optimization algorithms to test the performance of different combinations. A truss structure was numerically analyzed, and the response was adopted as a training and validation dataset. Dick *et al*. (2019) developed a proof-of-concept deep learning and vision based system to assess the state of the security of the energy infrastructure. The improvement of robust assessment including the ground truth data of the fine grained, the centralization of the data, and iterative model modification was discussed. Wu and Jahanshahi (2019) addressed a deep CNN-based approach to estimate the dynamic responses of three systems. The capacity for prediction of the proposed CNN was compared with an MLP, and different noise levels were added into the acceleration data for comparative study. Oh *et al*. (2019) proposed a CNN-based architecture to predict strain levels of tall buildings under wind loadings. The training dataset containing displacements and wind speeds was collected from a wind tunnel test of a model of a steel structure. Lyu *et al*. (2019) proposed a deep belief network-based approach to assess the state of the health of offshore platforms. A model platform was fabricated and tested to collect the wave force, strain, and acceleration data to establish the dataset for the validation of the proposed method.

4. Challenges and trends of the deep learning-based SHM strategy

Deep learning-based approaches are growing rapidly and have been applied to a variety of SHM applications, including structural damage detection and structural condition assessment. However, some theoretical and technical challenges are still standing in the way of spreading the applications of deep learning-based approaches to the SHM of civil infrastructures. Several major challenges are presented as follows:

(i) The dataset is extremely important in the training process of a DNN. For example, in the case of crack detection, a VGG-16 has more than 100 million parameters to be modified which requires thousands of labeled images for training. However, the images from inspectors are unlabeled and scattered at the hand of big or small inspection companies, and image sizes vary a lot depending on the digital cameras used. Also, the training dataset is expected to contain complicated real-world situations; otherwise misjudgment might occur during the testing of image classification from on-site inspections. Thus, a large amount of collecting, selecting, cleaning, and labeling work is inevitable for establishing an efficient image dataset. There are some techniques available to expand limited numbers of image data such as cropping, stretching, and adding salt and pepper noise. However, the image datasets for the training of DNNs for an SHM of civil infrastructures are still not enough.

(ii) Over-fitting is also a problem that needs to be solved when millions of parameters are to be modified in a deep architecture. For instance, the lack of enough training samples for structural damage detection will lead to over extraction of irrelevant features such as environmental noise. Increasing the sample numbers by expanding techniques will not work efficiently if training samples cannot reflect the real-world situation well, especially for image-based structural damage detection under multiple environmental conditions. The existing techniques, e.g., dropout, batch normalization, data cleaning, etc., will help, but efficient measures are still needed.

(iii) Interpretability is another problem troubling scholars and engineers for understanding the mechanism of deep learning-based approaches. The processing of DNNs is a black box which lacks of theoretical background and contains many kinds of uncertainties that cannot be clearly explained. For example, even though the decoding of feature maps in CNNs reveals that the CNN architecture will detect edges in the preliminary layers, the latter layers will eventually combine feature maps of edges to form motifs (LeCun *et al*. 2015). When it comes to designing a DNN for SHM application, problems such as what kind of kernels, how many layers or what kind of combinations should be adopted for efficient training and robust performance are still puzzling. To build a DNN with a satisfying performance, multiple times of training and validation are needed.

(iv) The ability for generalization is also a problem requiring further investigation. The DNNs, after repeated training and validation, might perform well for a single purpose. For example, a network for the detection of steel cracks might not work well to detect concrete cracks. This is because the concrete surface will contain many kinds of noises, e.g., spalling and calcification, and its crack edge is not identical to that of steel. A neural network for the detection of wind data anomaly might fail in the anomaly detection for earthquake monitoring data due to different patterns of anomalies. Transfer learning is a good method for improving the generalization ability, but novel theories and algorithms are far from enough to better improve the ability for broader SHM applications.

(v) Requirements for high performance hardware increase the cost for deploying deep learning-based approaches for SHM systems. To adequately train a DNN, repeated training with massive data is required. To store the massive data, especially images and videos, hard disks with a large volume are required. To implement the training process, multiple GPU, CPU and a large capacity memory are required. Extra computing and storage hardware is required, such as high performance workstations, servers or cloud computing platforms. Thus, DNNs with fewer parameters and efficient training strategies are needed to speed up the training process and reduce the cost for the deployment of deep learning-based approaches for SHM.

Despite so many challenges in the development of deep learning-based approaches, they are still promising tools for SHM. As time goes by, datasets based on the real world situation will be established, and unsupervised training algorithms will be developed to fully make use of the data obtained from SHM systems. New model architectures such as the Capsule network will be developed to provide a better capacity for feature extraction and detection to deal with different SHM scenarios. Combination of deep learning-based approaches with mobile devices (UAV) will be developed to provide better on-site detection for all kinds of civil infrastructures. Besides, the deep learning-based approaches will be integrated into an SHM system to provide timely and accurate structural damage detection and condition assessment, and this will certainly benefit the long-term SMM. Meanwhile, cloud computing and big data will be adopted to process the tremendous accumulation of monitoring data for the realization of deep learning-based recognition and classification with a higher efficiency. To consolidate and enlarge the deep learning-based SHM applications, joint efforts are required from scholars and engineers of computer science, civil engineering, etc., to establish a complete chain of data collection, algorithm development, hardware development and field applications. Deep learning-based approaches will play a more important role in the field of SHM to fulfill more complicated tasks including multiple damage detection and evaluation, structural condition assessment, structural behavior prediction, big data mining, etc.

5. Conclusions

This paper presented an overview of the recent research and development of deep learning for the SHM of civil infrastructures. Based on the comprehensive investigation of deep learning-based approaches, cases of application, challenging issues, the following conclusions can be made: (i) the development of deep learning including novel architectures, efficient training and validation algorithms, new frameworks, etc., will provide easier and more powerful data processing approaches for scholars and engineers to deal with professional issues; (ii) the main applications of deep learning-based approaches for the SHM of civil infrastructures are structural damage detection and structural condition assessment. Among them, vision-based applications draw great attention from the research community; (iii) overcoming challenges in the applications of the deep learning-based approaches to SHM requires the collection of specific datasets, the development of new architectures for better performance, and novel training strategies to release issues such as over-fitting and gradient vanishing. The deep learning-based approaches have been proven to have significant value for dealing with various kinds of SHM problems. With the development of new algorithms and frameworks, the establishment of sufficient datasets, and the improvement of computing power, deep learning-based approaches will significantly promote advances in the SHM research and applications.

Acknowledgments

The work described in this paper was jointly supported by the National Science Foundation of China (Grant Nos. 51822810 and 51778574), the Zhejiang Provincial Natural Science Foundation of China (Grant No. LR19E080002), the Fundamental Research Funds for the Central Universities of China (Grant No. 2019XZZX004-01), and the Key Research and Development Plan of Zhejiang Province (Grant No. 2017C03020).

References

Abdeljaber, O., Avci, O., Kiranyaz, S., Gabbouj, M. and Inman, D.J. (2017), "Real-time vibration-based structural damage detection using one-dimensional convolutional neural networks", *J. Sound. Vib.*, **388**, 154-170. DOI: 10.1016/j.jsv.2016.10.043.

Adeli, H. (2001), "Neural networks in civil engineering: 1989-2000", *Comput.-Aided Civil Infrastruct. Eng.*, **16**(2), 126-142. DOI: 10.1111/0885-9507.00219.

Adeli, H. and Yeh, C. (1989), "Perceptron learning in engineering design", *Comput.-Aided Civil Infrastruct. Eng.*, **4**(4), 247-256. DOI: 10.1111/j.1467-8667.1989.tb00026.x.

Alipour, M., Harris, D.K. and Miller, G.R. (2019), "Robust pixel-level crack detection using deep fully convolutional neural networks", *J. Comput. Civil. Eng.*, **33**(6), 04019040. DOI: 10.1061/(Asce)Cp.1943-5487.0000854.

Atha, D.J. and Jahanshahi, M.R. (2018), "Evaluation of deep learning approaches based on convolutional neural networks for corrosion detection", *Struct. Health. Monit.*, **17**(5), 1110-1128. DOI: 10.1177/1475921717737051.

Badrinarayanan, V., Kendall, A. and Cipolla, R. (2017), "SegNet: a deep convolutional encoder-decoder architecture for image segmentation", *IEEE Trans. Pattern Anal. Mach. Intell.*, **39**(12), 2481-2495. DOI: 10.1109/Tpami.2016.2644615.

Bang, S., Park, S., Kim, H. and Kim, H. (2019), "Encoder-decoder network for pixel-level road crack detection in black-box images", *Comput.-Aided Civil Infrastruct. Eng.*, **34**(8), 713-727. DOI: 10.1111/mice.12440.

Bao, Y.Q., Tang, Z.Y., Li, H. and Zhang, Y.F. (2019), "Computer vision and deep learning-based data anomaly detection method for structural health monitoring", *Struct. Health Monit.*, **18**(2), 401-421. DOI: 10.1177/1475921718757405.

Beckman, G.H., Polyzois, D. and Cha, Y.J. (2019), "Deep learning-based automatic volumetric damage quantification using depth camera", *Automat. Constr.*, **99**, 114-124. DOI: 10.1016/j.autcon.2018.12.006.

Bishop, C.M. (2006), *Pattern Recognition and Machine Learning*, Springer, New York, NY, USA.

Ceylan, H., Bayrak, M.B. and Gopalakrishnan, K. (2014), "Neural networks applications in pavement engineering: a recent survey", *Intl. J. Pavement Res. Tech.*, **7**(6), 434-444. DOI: 10.6135/ijprt.org.tw/2014.7(6).434.

Cha, Y.J., Choi, W. and Buyukozturk, O. (2017), "Deep learning-based crack damage detection using convolutional neural networks", *Comput.-Aided Civil Infrastruct. Eng.*, **32**(5), 361-378. DOI: 10.1111/mice.12263.

Cha, Y.J., Choi, W., Suh, G., Mahmoudkhani, S. and Buyukozturk, O. (2018), "Autonomous structural visual inspection using region-based deep learning for detecting multiple damage types", *Comput.-Aided Civil Infrastruct. Eng.*, **33**, 731-747. DOI: 10.1111/mice.12334.

Chellapilla, K., Puri, S. and Simard, P. (2006), "High performance convolutional neural networks for document processing", *Proceedings of the 10th International Workshop on Frontiers in Handwriting Recognition*, La Baule, France (CD-ROM).

Chen, F.C. and Jahanshahi, M.R. (2018), "NB-CNN: deep learning-based crack detection using convolutional neural network and naive bayes data fusion", *IEEE T.. Ind. Electron.*, **65**(5), 4392-4400. DOI: 10.1109/Tie.2017.2764844.

Chen, L.C., Papandreou, G., Kokkinos, I., Murphy, K. and Yuille, A.L. (2018), "DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs", *IEEE T. Pattern Anal. Mach. Intell.*, **40**(4), 834-848. DOI: 10.1109/Tpami.2017.2699184.

Chen, X., Duan, Y., Houthooft, R., Schulman, J., Sutskever, I. and Abbeel, P. (2016), "InfoGAN: interpretable representation learning by information maximizing generative adversarial nets", *Proceedings of the 30th Conference on Neural Information Processing Systems,* Barcelona, Spain (CD-ROM).

Cheng, J.C.P. and Wang, M.Z. (2018), "Automated detection of sewer pipe defects in closed-circuit television images using deep learning techniques", *Automat. Constr.*, **95**, 155-171. DOI: 10.1016/j.autcon.2018.08.006.

Cho, S., Yun, C.B. and Sim, S.H. (2015), "Displacement estimation of bridge structures using data fusion of acceleration and strain measurement incorporating finite element model", *Smart. Struct. Syst.*, **15**(3), 645-663. https://doi.org/10.12989/sss.2015.15.3.645.

Ciresan, D.C., Meier, U., Gambardella, L.M. and Schmidhuber, J. (2010), "Deep, big, simple neural nets for handwritten digit recognition", *Neural Comput.*, **22**(12), 3207-3220. DOI: 10.1162/Neco_a_00052.

DeVries, P.M.R., Viegas, F., Wattenberg, M. and Meade, B.J. (2018), "Deep learning of aftershock patterns following large earthquakes", *Nature*, **560**(7720), 632-634. DOI: 10.1038/s41586-018-0438-y.

Dick, K., Russell, L., Dosso, Y.S., Kwamena, F. and Green, J.R. (2019), "Deep learning for critical infrastructure resilience", *J. Infrastruct. Syst.*, **25**(2), 05019003. DOI: 10.1061/(Asce)Is.1943-555x.0000477.

Dinh, K., Gucunski, N. and Duong, T.H. (2018), "An algorithm for automatic localization and detection of rebars from GPR data of concrete bridge decks", *Automat. Constr.*, **89**, 292-298. DOI: 10.1016/j.autcon.2018.02.017.

Dong, C., Loy, C.C., He, K.M. and Tang, X.O. (2016), "Image super-resolution using deep convolutional networks", *IEEE Trans. Pattern Anal. Mach. Intell.*, **38**(2), 295-307. DOI: 10.1109/Tpami.2015.2439281.

Dong, C.Z., Ye, X.W. and Jin, T. (2018), "Identification of structural dynamic characteristics based on machine vision technology", *Measurement*, **126**, 405-416. DOI: 10.1016/j.measurement.2017.09.043.

Dorafshan, S., Thomas, R.J. and Maguire, M. (2018), "Comparison of deep convolutional neural networks and edge detectors for image-based crack detection in concrete", *Constr. Build. Mater.*, **186**, 1031-1045. DOI: 10.1016/j.conbuildmat.2018.08.011.

Duan, Y.F., Chen, Q.Y., Zhang, H.M., Yun, C.B., Wu, S.K. and Zhu, Q. (2019), "CNN-based damage identification method of tied-arch bridge using spatial-spectral information", *Smart. Struct. Syst.*, **23**(5), 507-520. https://doi.org/10.12989/sss.2019.23.5.507.

Dung, C.V. and Anh, L.D. (2019), "Autonomous concrete crack detection using deep fully convolutional neural network", *Automat. Constr.*, **99**, 52-58. DOI: 10.1016/j.autcon.2018.11.028.

Dung, C.V., Sekiya, H., Hirano, S., Okatani, T. and Miki, C. (2019), "A vision-based method for crack detection in gusset plate welded joints of steel bridges using deep convolutional neural networks", *Automat. Constr.*, **102**, 217-229. DOI: 10.1016/j.autcon.2019.02.013.

Elman, J.L. (1990), "Finding structure in time", *Cogn. Sci.*, **14**(2), 179-211. DOI: 10.1207/s15516709cog1402_1.

Fan, G., Li, J. and Hao, H. (2019), "Lost data recovery for structural health monitoring based on convolutional neural networks", *Struct. Control. Health Monit*., **26**(10), e2433. DOI: 10.1002/Stc.2433.

Feng, D.M. and Feng, M.Q. (2018), "Computer vision for SHM of civil infrastructure: from dynamic response measurement to damage detection - a review", *Eng. Struct.*, **156**, 105-117. DOI: 10.1016/j.engstruct.2017.11.018.

Gao, X.W., Jian, M., Hu, M., Tanniru, M. and Li, S.Q. (2019), "Faster multi-defect detection system in shield tunnel using combination of FCN and Faster RCNN", *Adv. Struct. Eng.*, **22**(13), 2907-2921. DOI: 10.1177/1369433219849829.

Gao, Y. and Spencer, B.F. (2007), "Experimental verification of a distributed computing strategy for structural health monitoring", *Smart. Struct. Syst.*, **3**(4), 455-474. DOI: 10.12989/sss.2007.3.4.455.

Gao, Y.Q., Kong, B.Y. and Mosalam, K.M. (2019), "Deep leaf-bootstrapping generative adversarial network for structural image data augmentation", *Comput.-Aided Civil Infrastruct. Eng*., **34**(9), 755-773. DOI: 10.1111/mice.12458.

Gao, Y.Q. and Mosalam, K.M. (2018), "Deep transfer learning for image-based structural damage recognition", *Comput.-Aided Civil Infrastruct. Eng.*, **33**(9), 748-768. DOI: 10.1111/mice.12363.

Gibert, X., Patel, V. and Chellappa, R. (2017), "Deep multitask learning for railway track inspection", *IEEE T. Intell. Transp. Syst.*, **18**(1), 153-164. DOI: 10.1109/Tits.2016.2568758.

Girshick, R., Donahue, J., Darrell, T. and Malik, J. (2014), "Rich feature hierarchies for accurate object detection and semantic segmentation", *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*", Columbus, USA (CD-ROM).

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y. (2014), "Generative adversarial nets", *Proceedings of the International Conference on Neural Information Processing Systems*, Montreal, Canada (CD-ROM).

Goodfellow, I., Bengio, Y. and Courville, A. (2016), *Deep Learning*, MIT Press, Boston, MA, USA.

Gopalakrishnan, K., Khaitan, S.K., Choudhary, A. and Agrawal, A. (2017), "Deep convolutional neural networks with transfer learning for computer vision-based data-driven pavement distress detection", *Constr. Build. Mater.*, **157**, 322-330. DOI: 10.1016/j.conbuildmat2017.09.110.

Gulgec, N.S., Takac, M. and Pakzad, S.N. (2019), "Convolutional neural network approach for robust structural damage detection and localization", *J. Comput. Civil. Eng.*, **33**(3), 04019005. DOI: 10.1061/(Asce)Cp.1943-5487.0000820.

Hakim, S.J.S. and Razak, H.A. (2014), "Modal parameters based structural damage detection using artificial neural networks - a review", *Smart. Struct. Syst.*, **14**(2), 159-189. https://doi.org/10.12989/sss.2014.14.2.159.

He, K.M., Zhang, X.Y., Ren, S.Q. and Sun, J. (2016), "Deep residual learning for image recognition", *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegas, USA (C-ROM).

Hinton, G.E., Krizhevsky, A. and Wang, S.D. (2011), "Transforming auto-encoders", *Proceedings of the 21st International Conference on Artificial Neural Networks*, Espoo, Finland (CD-ROM).

Hinton, G.E., Osindero, S. and Teh, Y.W. (2006), "A fast learning algorithm for deep belief nets", *Neural Comput.*, **18**(7), 1527-1554. DOI: 10.1162/neco.2006.18.7.1527.

Hinton, G.E. and Salakhutdinov, R.R. (2006), "Reducing the dimensionality of data with neural networks", *Science*, **313**(5786), 504-507. DOI: 10.1126/science.1127647.

Hoang, N.D., Nguyen, Q.L. and Tran, V.D. (2018), "Automatic recognition of asphalt pavement cracks using metaheuristic optimized edge detection algorithms and convolution neural network", *Automat. Constr.*, **94**, 203-213. DOI: 10.1016/j.autcon.2018.07.008.

Hochreiter, S. and Schmidhuber, J. (1997), "Long short-term memory", *Neural Comput*, **9**(8), 1735-1780. DOI: 10.1162/neco.1997.9.8.1735.

Hopfield, J.J. (1982), "Neural networks and physical systems with emergent collective computational abilities", *Proc. Natl. Acad. Sci. USA.*, **79**(8), 2554-2558. DOI: 10.1073/pnas.79.8.2554.

Howard, A.G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M. and Adam, H. (2017), "Mobilenets: efficient convolutional neural networks for mobile vision applications", *arXiv preprint arXiv:1704.04861*.

Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K.Q. (2017), "Densely connected convolutional networks", *Proceedings of the 30th IEEE Conference on Computer Vision and Pattern Recognition*", Honolulu, USA (CD-ROM).

Huang, H.W., Li, Q.T. and Zhang, D.M. (2018), "Deep learning based image recognition for crack and leakage defects of metro shield tunnel", *Tunn. Undergr. Sp. Tech.*, **77**, 166-176. DOI: 10.1016/j.tust.2018.04.002.

Huynh, T.C., Park, J.H., Jung, H.J. and Kim, J.T. (2019), "Quasi-autonomous bolt-loosening detection method using vision-based deep learning and image processing", *Automat. Constr.*, **105**, UNSP 102844. DOI: 10.1016/J.Autcon.2019.102844.

Jang, S., Jo, H., Cho, S., Mechitov, K., Rice, J.A., Sim, S.H., Jung, H.J., Yun, C.B., Spencer, B.F. and Agha, G. (2010), "Structural health monitoring of a cable-stayed bridge using smart sensor technology: deployment and evaluation", *Smart. Struct. Syst.*, **6**(5-6), 439-459. https://doi.org/ 10.12989/sss.2010.6.5_6.439.

Kang, D.H. and Cha, Y.J. (2018), "Autonomous UAVs for structural health monitoring using deep learning and an ultrasonic beacon system with geo-tagging", *Comput.-Aided Civil Infrastruct. Eng.*, **33**(10), 885-902. DOI: 10.1111/mice.12375.

Kang, G.Q., Gao, S.B., Yu, L. and Zhang, D.K. (2019), "Deep architecture for high-speed railway insulator surface defect detection: denoising autoencoder with multitask learning", *IEEE T. Instrum. Meas.*, **68**(8), 2679-2690. DOI: 10.1109/Tim.2018.2868490.

Kesavan, K., Ravisankar, K., Parivallal, S. and Sreeshylam, P. (2005), "Applications of fiber optic sensors for structural health monitoring", *Smart. Struct. Syst.*, **1**(4), 355-368. https://doi.org/10.12989/sss.2005.1.4.355.

Khodabandehlou, H., Pekcan, G. and Fadali, M.S. (2019), "Vibration-based structural condition assessment using convolution neural networks", *Struct. Control. Health Monit.*, **26**(2), e2308. DOI: 10.1002/Stc.2308.

Kim, B. and Cho, S. (2018), "Automated vision-based detection of cracks on concrete surfaces using a deep learning technique", *Sensors*, **18**(10), 3452. DOI: 10.3390/S18103452.

Kim, B. and Cho, S. (2019), "Image-based concrete crack assessment using mask and region-based convolutional neural network", *Struct. Control. Health Monit.*, **26**(8), e2381. DOI: 10.1002/Stc.2381.

Kim, H. and Sim, S.H. (2019), "Automated peak picking using region-based convolutional neural network for operational modal analysis", *Struct. Control. Health Monit.*, e2436. DOI: 10.1002/Stc.2436.

Kim, I.H., Jeon, H., Baek, S.C., Hong, W.H. and Jung, H.J. (2018), "Application of crack identification techniques for an aging concrete bridge inspection using an unmanned aerial vehicle", *Sensors*, **18**(6), 1881. DOI: 10.3390/S18061881.

Krizhevsky, A., Sutskever, I. and Hinton, G.E. (2012), "ImageNet classification with deep convolutional neural networks", *Proceedings of the 26th Annual Conference on Neural Information Processing Systems*, Lake Tahoe, USA (CD-ROM).

Kumar, S.S., Abraham, D.M., Jahanshahi, M.R., Iseley, T. and Starr, J. (2018), "Automated defect classification in sewer closed circuit television inspections using deep convolutional neural networks", *Automat. Constr.*, **91**, 273-283. DOI: 10.1016/j.autcon.2018.03.028.

Lake, B.M., Salakhutdinov, R. and Tenenbaum, J.B. (2015), "Human-level concept learning through probabilistic program induction", *Science*, **350**(6266), 1332-1338. DOI: 10.1126/science.aab3050.

LeCun, Y., Boser, B., Denker, J.S., Henderson, D., Howard, R.E., Hubbard, W. and Jackel, L.D. (1989), "Backpropagation applied to handwritten zip code recognition", *Neural Comput.*, **1**(4), 541-551. DOI: 10.1162/neco.1989.1.4.541.

LeCun, Y., Bottou, L., Bengio, Y. and Haffner, P. (1998), "Gradient-based learning applied to document recognition", *Proc. IEEE*, **86**(11), 2278-2324. DOI: 10.1109/5.726791.

LeCun, Y., Bengio, Y. and Hinton, G. (2015), "Deep learning", *Nature*, **521**(7553), 436-444. DOI: 10.1038/nature14539.

Lee, S., Ha, J., Zokhirova, M., Moon, H. and Lee, J. (2018), "Background information of deep learning for structural engineering", *Arch. Comput. Method E.*, **25**(1), 121-129. DOI: 10.1007/s11831-017-9237-0.

Li, C., Xu, P.J., Niu, L.J.L., Chen, Y., Sheng, L.S. and Liu, M.C. (2019), "Tunnel crack detection using coarse-to-fine region localization and edge detection", *Wiley Interdiscip. Rev.-Data Mining Knowl. Discov.*, **9**(5), e1308. DOI:10.1002/Widm.1308.

Li, D.S., Cong, A.R. and Guo, S. (2019), "Sewer damage detection from imbalanced CCTV inspection data using deep convolutional neural networks with hierarchical classification", *Autom. Constr.*, **101**, 199-208. DOI: 10.1016/j.autcon.2019.01.017.

Li, R.X., Yuan, Y.C., Zhang, W. and Yuan, Y.L. (2018), "Unified vision-based methodology for simultaneous concrete defect detection and geolocalization", *Comput.-Aided Civil Infrastruct. Eng.*, **33**(7), 527-544. DOI: 10.1111/mice.12351.

Li, S.L., Guo, Y.P., Xu, Y. and Li, Z.L. (2019), "Real-time geometry identification of moving ships by computer vision techniques in bridge area", *Smart. Struct. Syst.*, **23**(4), 359-371. https://doi.org/10.12989/sss.2019.23.4.359.

Li, S.Y., Zhao, X.F. and Zhou, G.Y. (2019), "Automatic pixel-level multiple damage detection of concrete structure using fully convolutional network", *Comput.-Aided Civil Infrastruct. Eng.*, **34**(7), 616-634. DOI: 10.1111/mice.12433.

Liang, X. (2019), "Image-based post-disaster inspection of reinforced concrete bridge systems using deep learning with Bayesian optimization", *Comput.-Aided Civil Infrastruct. Eng.*, **34**(5), 415-430. DOI: 10.1111/mice.12425.

Liang, Y., Wu, D.L., Liu, G.R., Li, Y.H., Gao, C.L., Ma, Z.G.J. and Wu, W.D. (2016), "Big data-enabled multiscale serviceability analysis for aging bridges", *Digit. Commun. Netw.*, **2**(3), 97-107. DOI: 10.1016/j.dcan.2016.05.002.

Lin, G.S., Milan, A., Shen, C.H. and Reid, I. (2017), "RefineNet: multi-path refinement networks for high-resolution semantic segmentation", *Proceedings of the 30th IEEE Conference on Computer Vision and Pattern Recognition*", Honolulu, USA, (CD-ROM).

Lin, Y.Z., Nie, Z.H. and Ma, H.W. (2017), "Structural damage detection with automatic feature-extraction through deep learning", *Comput.-Aided Civil Infrastruct. Eng.*, **32**(12), 1025-1046. DOI: 10.1111/mice.12313.

Liu, H. and Zhang, Y.F. (2019), "Image-driven structural steel damage condition assessment method using deep learning algorithm", *Measurement*, **133**, 168-181. DOI: 10.1016/j.measurement.2018.09.081.

Liu, J.B., Huang, Y.P., Zou, Q., Tian, M., Wang, S.C., Zhao, X.X., Dai, P. and Ren, S.W. (2019), "Learning visual similarity for inspecting defective railway fasteners", *IEEE Sens. J.*, **19**(16), 6844-6857. DOI: 10.1109/Jsen.2019.2911015.

Liu, J.T., Yang, X.X. and Li, L. (2019), "VibroNet: recurrent neural networks with multi-target learning for image-based vibration frequency measurement", *J. Sound Vib.*, **457**, 51-66. DOI: 10.1016/j.jsv.2019.05.027.

Lyu, T., Xu, C.H., Chen, G.M., Li, Q.Y., Zhao, T.T. and Zhao, Y.P. (2019), "Health state inversion of jack-up structure based on feature learning of damage information", *Eng. Struct.*, **186**, 131-145. DOI: 10.1016/j.engstruct.2019.02.004.

Maeda, H., Sekimoto, Y., Seto, T., Kashiyama, T. and Omata, H. (2018), "Road damage detection and classification using deep neural networks with smartphone images", *Comput.-Aided Civil Infrastruct. Eng.*, **33**(12), 1127-1141. DOI: 10.1111/mice.12387.

Matos, J.C.E., Garcia, O., Henriques, A.A., Casas, J.R. and Vehi, J. (2009), "Health monitoring system (HMS) for structural assessment", *Smart. Struct. Syst.*, **5**(3), 223-240. https://doi.org/10.12989/sss.2009.5.3.223.

Mcculloch, W.S. and Pitts, W. (1943), "A logical calculus of the ideas immanent in nervous activity", *B. Math. Biol.*, **5**, 115-133. DOI: 10.1007/BF02478259.

Min, J., Park, S. and Yun, C.B. (2010), "Impedance-based structural health monitoring using neural networks for autonomous frequency range selection", *Smart Mater. Struct.*, **19**(12), 125011. DOI: 10.1088/0964-1726/19/12/125011.

Min, J., Yi, J.H. and Yun, C.B. (2015), "Electromechanical impedance-based long-term SHM for jacket-type tidal current power plant structure", *Smart. Struct. Syst.*, **15**(2), 283-297. https://doi.org/10.12989/sss.2015.15.2.283.

Ni, F.T., Zhang, J. and Chen, Z.Q. (2019), "Pixel-level crack delineation in images with convolutional feature fusion", *Struct. Control. Health Monit.*, **26**(1), e2286. DOI: 10.1002/Stc.2286.

Ni, F.T., Zhang, J. and Chen, Z.Q. (2019), "Zernike-moment measurement of thin-crack width in images enabled by dual-scale deep learning", *Comput.-Aided Civil Infrastruct. Eng.*, **34**(5), 367-384. DOI: 10.1111/mice.12421.

Ni, Y.Q., Wang, B.S. and Ko, J.M. (2002), "Constructing input vectors to neural networks for structural damage identification", *Smart Mater. Struct.*, **11**(6), 825-833. DOI: 10.1088/0964-1726/11/6/301.

Ni, Y.Q., Ye, X.W. and Ko, J.M. (2010), "Monitoring-based fatigue reliability assessment of steel bridges: Analytical model and application", *J. Struct. Eng.*, **136**(12), 1563-1573. DOI: 10.1061/(Asce)St.1943-541x.0000250.

Ni, Y.Q., Ye, X.W. and Ko, J.M. (2012), "Modeling of stress spectrum using long-term monitoring data and finite mixture distributions", *J. Eng. Mech.*, **138**(2), 175-183. DOI: 10.1061/(Asce)Em.1943-7889.0000313.

Noh, H., Hong, S. and Han, B. (2015), "Learning deconvolution network for semantic segmentation", *Proceedings of the IEEE International Conference on Computer Vision*, Santiago, Chile (CD-ROM).

Nowozin, S., Cseke, B. and Tomioka, R. (2016), "*f*-GAN: training generative neural samplers using variational divergence minimization", *Proceedings of the 30th Conference on Neural Information Processing Systems,* Barcelona, Spain (CD-ROM).

Oh, B.K., Glisic, B., Kim, Y. and Park, H.S. (2019), "Convolutional neural network-based wind-induced response estimation model for tall buildings", *Comput.-Aided Civil Infrastruct. Eng.*, **34**(10), 843-858. DOI: 10.1111/mice.12476.

Onat, O. and Gul, M. (2018), "Application of artificial neural networks to the prediction of out-of-plane response of infill walls subjected to shake table", *Smart. Struct. Syst.*, **21**(4), 521-535. https://doi.org/10.12989/sss.2018.21.4.521.

Park, S., Bang, S., Kim, H. and Kim, H. (2019), "Patch-based crack detection in black box images using convolutional neural networks", *J. Comput. Civil. Eng.*, **33**(3), 04019017. DOI: 10.1061/(Asce)Cp.1943-5487.0000831.

Paszke, A., Chaurasia, A., Kim, S. and Culurciello, E. (2016). "Enet: a deep neural network architecture for real-time semantic segmentation", *arXiv preprint arXiv:1606.02147*.

Pathirage, C.S.N., Li, J., Li, L., Hao, H., Liu, W.Q. and Ni, P.H. (2018), "Structural damage identification based on autoencoder neural networks and deep learning", *Eng. Struct.*, **172**, 13-28. DOI: 10.1016/j.engstruct.2018.05.109.

Rafiei, M.H. and Adeli, H. (2018), "A novel unsupervised deep learning model for global and local health condition assessment of structures", *Eng. Struct.*, **156**, 598-607. DOI: 10.1016/j.engstruct.2017.10.070.

Raina, R., Madhavan, A. and Ng, A.Y. (2009), "Large-scale deep unsupervised learning using graphics processors", *Proceedings of the 26th Annual International Conference on Machine Learning*, Montreal, Canada (CD-ROM).

Ren, S.Q., He, K.M., Girshick, R. and Sun, J. (2015), "Faster R-CNN: towards real-time object detection with region proposal networks", *Proceedings of the 29th Annual Conference on Neural Information Processing Systems*, Montreal, Canada (CD-ROM).

Ronneberger, O., Fischer, P. and Brox, T. (2015), "U-Net: convolutional networks for biomedical image segmentation", *Proceedings of the 18th International Conference on Medical Image Computing and Computer Assisted Intervention*, Munich, Germany (CD-ROM).

Rosenblatt, F. (1958), "The perceptron - a probabilistic model for information-storage and organization in the brain", *Psychol. Rev.*, **65**(6), 386-408. DOI: 10.1037/H0042519.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J. (1986), "Learning representations by back-propagating errors", *Nature*, **323**(6088), 533-536. DOI: 10.1038/323533a0.

Russell, S.J. and Norvig, P. (2016), *Artificial Intelligence: A Modern Approach*, Pearson Education Limited, Harlow, England, UK.

Sabour, S., Frosst, N. and Hinton, G.E. (2017), "Dynamic routing between capsules", *Proceedings of the 31st Conference on Neural Information Processing Systems*, Long Beach, USA (CD-ROM).

Sajedi, S.O. and Liang, X. (2019), "A convolutional cost-sensitive crack localization algorithm for automated and reliable RC bridge inspection", *arXiv preprint arXiv:1905.09716*.

Salehi, H. and Burgueno, R. (2018), "Emerging artificial intelligence methods in structural engineering", *Eng. Struct.*, **171**, 170-189. DOI: 10.1016/j.engstruct.2018.05.084.

Schmidhuber, J. (2015), "Deep learning in neural networks: an overview", *Neural Netw.*, **61**, 85-117. DOI: 10.1016/j.neunet.2014.09.003.

Shelhamer, E., Long, J. and Darrell, T. (2017), "Fully convolutional networks for semantic segmentation", *IEEE Trans. Pattern Anal. Mach. Intell.*, **39**(4), 640-651. DOI: 10.1109/Tpami.2016.2572683.

Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T. and Hassabis, D. (2016), "Mastering the game of Go with deep neural networks and tree search", *Nature*, **529**(7587), 484-489. DOI: 10.1038/nature16961.

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A., Chen, Y.T., Lillicrap, T., Hui, F., Sifre, L., Van Den Driessche, G., Graepel, T. and Hassabis, D. (2017), "Mastering the game of Go without human knowledge", *Nature*, **550**(7676), 354-359. DOI: 10.1038/nature24270.

Simonyan, K. and Zisserman, A. (2014), "Very deep convolutional networks for large-scale image recognition", *arXiv preprint arXiv:1409.1556*.

Song, Q., Wu, Y.Q., Xin, X.S., Yang, L., Yang, M., Chen, H.M., Liu, C., Hu, M.J., Chai, X.S. and Li, J.C. (2019), "Real-time tunnel crack analysis system via deep learning", *IEEE Access*, **7**, 64186-64197. DOI: 10.1109/Access.2019.2916330.

Sony, S., Laventure, S. and Sadhu, A. (2019), "A literature review of next-generation smart sensing technology in structural health monitoring", *Struct. Control. Health Monit.*, **26**(3), e2321. DOI: 10.1002/Stc.2321.

Spencer, B.F., Hoskere, V. and Narazaki, Y. (2019), "Advances in computer vision-based civil infrastructure inspection and monitoring", *Engineering*, **5**(2), 199-222. DOI: 10.1016/j.eng.2018.11.030.

Szegedy, C., Liu, W., Jia, Y.Q., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A. (2014), "Going deeper with convolutions", *arXiv preprint arXiv:1409.4842*.

Szewczyk, Z.P. and Hajela, P. (1994), "Damage detection in structures based on feature-sensitive neural networks", *J. Comput. Civil. Eng.*, **8**(2), 163-178. DOI: 10.1061/(Asce)0887-3801(1994)8:2(163).

Tang, Z.Y., Chen, Z.C., Bao, Y.Q. and Li, H. (2019), "Convolutional neural network-based data anomaly detection method using multiple information for structural health monitoring", *Struct. Control. Health Monit.*, **26**(1), e2296. DOI: 10.1002/Stc.2296.

Tong, Z., Gao, J. and Zhang, H.T. (2017), "Recognition, location, measurement, and 3D reconstruction of concealed cracks using convolutional neural networks", *Constr. Build. Mater.*, **146**, 775-787. DOI: 10.1016/j.conbuildmat.2017.04.097.

Tong, Z., Gao, J., Han, Z.Q. and Wang, Z.J. (2018), "Recognition of asphalt pavement crack length using deep convolutional neural networks", *Road Mater. Pavement Des.*, **19**(6), 1334-1349. DOI: 10.1080/14680629.2017.1308265.

Tong, Z., Gao, J., Sha, A.M., Hu, L.Q. and Li, S. (2018), "Convolutional neural network for asphalt pavement surface texture analysis", *Comput.-Aided Civil Infrastruct. Eng.*, **33**(12), 1056-1072. DOI: 10.1111/mice.12406.

Vodrahalli, K. and Bhowmik, A.K. (2017), "3D computer vision based on machine learning with deep neural networks: a review", *J. Soc. Inf. Disp.*, **25**(11), 676-694. DOI: 10.1002/jsid.617.

Wang, M.Z. and Cheng, J.C.P. (2019), "A unified convolutional neural network integrated with conditional random field for pipe defect segmentation", *Comput.-Aided Civil Infrastruct. Eng.*, DOI: 10.1111/mice.12481.

Wang, N.N., Zhao, Q.G., Li, S.Y., Zhao, X.F. and Zhao, P. (2018), "Damage classification for masonry historic structures using convolutional neural networks based on still images", *Comput.-Aided Civil Infrastruct. Eng.*, **33**(12), 1073-1089. DOI: 10.1111/mice.12411.

Wang, Z.Y., Zheng, H.R., Li, L.C., Liang, J.J., Wang, X., Lu, B., Ye, Q., Qu, R.H. and Cai, H.W. (2019), "Practical multi-class event classification approach for distributed vibration sensing using deep dual path network", *Opt. Express*, **27**(17), 23682-23692. DOI: 10.1364/Oe.27.023682.

Wei, X.K., Yang, Z.M., Liu, Y.X., Wei, D.H., Jia, L.M. and Li, Y.J. (2019), "Railway track fastener defect detection based on image processing and deep learning techniques: a comparative study", *Eng. Appl. Artif. Intell.*, **80**, 66-81. DOI: 10.1016/j.engappai.2019.01.008.

Weng, J.Y., McClelland, J., Pentland, A., Sporns, O., Stockman, I., Sur, M. and Thelen, E. (2001), "Artificial intelligence - autonomous mental development by robots and animals", *Science*, **291**(5504), 599-600. DOI: 10.1126/science.291.5504.599.

Wu, R.T. and Jahanshahi, M.R. (2019), "Deep convolutional neural network for structural dynamic response estimation and system identification", *J. Eng. Mech.*, **145**(1), 04018125. DOI: 10.1061/(Asce)Em.1943-7889.0001556.

Wu, R.T., Singla, A., Jahanshahi, M.R., Bertino, E., Ko, B.J. and Verma, D. (2019), "Pruning deep convolutional neural networks for efficient edge computing in condition assessment of infrastructures", *Comput.-Aided Civil Infrastruct. Eng.*, **34**(9), 774-789. DOI: 10.1111/mice.12449.

Wu, X., Ghaboussi, J. and Garrett, J.H. (1992), "Use of neural networks in detection of structural damage", *Comput. Struct.*, **42**(4), 649-659. DOI: 10.1016/0045-7949(92)90132-J.

Xu, Y., Wei, S.Y., Bao, Y.Q. and Li, H. (2019), "Automatic seismic damage identification of reinforced concrete columns from images by a region-based deep convolutional neural network", *Struct. Control. Health Monit.*, **26**(3), e2313. DOI: 10.1002/Stc.2313.

Xue, Y.D. and Li, Y.C. (2018), "A fast detection method via region-based fully convolutional neural networks for shield tunnel lining defects", *Comput.-Aided Civil Infrastruct. Eng.*, **33**(8), 638-654. DOI: 10.1111/mice.12367.

Yang, G.W., Li, Q.J., Zhan, Y., Fei, Y. and Zhang, A.N. (2018), "Convolutional neural network-based friction model using pavement texture data", *J. Comput. Civil Eng.*, **32**(6), 04018052. DOI: 10.1061/(Asce)Cp.1943-5487.0000797.

Yang, X.C., Li, H., Yu, Y.T., Luo, X.C., Huang, T. and Yang, X. (2018), "Automatic pixel-level crack detection and measurement using fully convolutional network", *Comput.-Aided Civil Infrastruct. Eng.*, **33**(12), 1090-1109. DOI: 10.1111/mice.12412.

Ye, X.W., Ni, Y.Q., Wong, K.Y. and Ko, J.M. (2012), "Statistical analysis of stress spectra for fatigue life assessment of steel bridges with structural health monitoring data", *Eng. Struct.*, **45**, 166-176. DOI: 10.1016/j.engstruct.2012.06.016.

Ye, X.W., Ni, Y.Q., Wai, T.T., Wong, K.Y., Zhang, X.M. and Xu, F. (2013), "A vision-based system for dynamic displacement measurement of long-span bridges: algorithm and verification", *Smart Struct. Syst.*, **12**(3-4), 363-379. https://doi.org/10.12989/sss.2013.12.3_4.363.

Ye, X.W., Yi, T.H., Dong, C.Z., Liu, T. and Bai, H. (2015), "Multi-point displacement monitoring of bridges using a vision-based approach", *Wind Struct.*, **20**(2), 315-326. https://doi.org/10.12989/was.2015.20.2.315.

Ye, X.W., Yi, T.H., Dong, C.Z. and Liu, T. (2016a), "Vision-based structural displacement measurement: system performance evaluation and influence factor analysis", *Measurement*, **88**, 372-384. DOI: 10.1016/j.measurement.2016.01.024.

Ye, X.W., Dong, C.Z. and Liu, T. (2016b), "Image-based structural dynamic displacement measurement using different multi-object tracking algorithms", *Smart. Struct. Syst.*, **17**(6), 935-956. DOI: 10.12989/sss.2016.17.6.935.

Ye, X.W., Dong, C.Z. and Liu, T. (2016c), "Force monitoring of steel cables using vision-based sensing technology: methodology and experimental verification", *Smart. Struct. Syst.*, **18**(3), 585-599. https://doi.org/10.12989/sss.2016.18.3.585.

Ye, X.W., Jin, T. and Chen, P.Y. (2019). "Structural crack detection using deep learning-based fully convolutional networks", *Adv. Struct. Eng.*, DOI: 10.1177/1369433219836292.

Yeum, C.M., Dyke, S.J. and Ramirez, J. (2018), "Visual data classification in post-event building reconnaissance", *Eng. Struct.*, **155**, 16-24. DOI: 10.1016/j.engstruct.2017.10.057.

Yeum, C.M., Choi, J. and Dyke, S.J. (2019), "Automated region-of-interest localization and classification for vision-based visual assessment of civil infrastructure", *Struct. Health Monit.*, **18**(3), 675-689. DOI: 10.1177/1475921718765419.

Yu, Y., Wang, C.Y., Gu, X.Y. and Li, J.C. (2019), "A novel deep learning-based method for damage identification of smart building structures", *Struct. Health Monit.*, **18**(1), 143-163. DOI: 10.1177/1475921718804132.

Yun, C.B. and Bahng, E.Y. (2000), "Substructural identification using neural networks", *Comput. Struct.*, **77**(1), 41-52. DOI: 10.1016/S0045-7949(99)00199-6.

Zeiler, M.D. and Fergus, R. (2014), "Visualizing and understanding convolutional networks", *Proceedings of the European Conference on Computer Vision*, Zurich, Switzerland, (CD-ROM).

Zhang, A., Wang, K.C.P., Li, B.X., Yang, E.H., Dai, X.X., Peng, Y., Fei, Y., Liu, Y., Li, J.Q. and Chen, C. (2017), "Automated pixel-level pavement crack detection on 3D asphalt surfaces using a deep-learning network", *Comput.-Aided Civil Infrastruct. Eng.*, **32**(10), 805-819. DOI: 10.1111/mice.12297.

Zhang, A., Wang, K.C.P., Fei, Y., Liu, Y., Tao, S.Y., Chen, C., Li, J.Q. and Li, B.X. (2018), "Deep learning-based fully automated pavement crack detection on 3D asphalt surfaces with an improved CrackNet", *J. Comput. Civil Eng.*, **32**(5), 4018041. DOI: 10.1061/(Asce)Cp.1943-5487.0000775.

Zhang, A., Wang, K.C.P., Fei, Y., Liu, Y., Chen, C., Yang, G.W., Li, J.Q., Yang, E.H. and Qiu, S. (2019), "Automated pixel-level pavement crack detection on 3D asphalt surfaces with a recurrent neural network", *Comput.-Aided Civil Infrastruct. Eng.*, **34**(3), 213-229. DOI: 10.1111/mice.12409.

Zhang, B., Zhou, L.M. and Zhang, J. (2019), "A methodology for obtaining spatiotemporal information of the vehicles on bridges based on computer vision", *Comput.-Aided Civil Infrastruct. Eng.*, **34**(6), 471-487. DOI: 10.1111/mice.12434.

Zhang, J.M., Lu, C.Q., Wang, J., Wang, L. and Yue, X.G. (2019), "Concrete cracks detection based on FCN with dilated convolution", *Appl. Sci.-Basel*, **9**(13), 2686. DOI: 10.3390/App9132686.

Zhang, K.G., Cheng, H.D. and Zhang, B.Y. (2018), "Unified approach to pavement crack and sealed crack detection using preclassification based on transfer learning", *J. Comput. Civil. Eng.*, **32**(2), 04018001. DOI: 10.1061/(Asce)Cp.1943-5487.0000736.

Zhang, X., Zhou, X.Y., Lin, M.X. and Sun, R. (2018), "ShuffleNet: an extremely efficient convolutional neural network for mobile devices", *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*", Salt Lake City, USA (CD-ROM).

Zhang, X.X., Rajan, D. and Story, B. (2019), "Concrete crack detection using context-aware deep semantic segmentation network", *Comput.-Aided Civil Infrastruct. Eng.*, DOI: 10.1111/mice.12477.

Zhang, Y.Q., Miyamori, Y., Mikami, S. and Saito, T. (2019), "Vibration-based structural state identification by a 1-dimensional convolutional neural network", *Comput.-Aided Civil Infrastruct. Eng.*, **34**(9), 822-839. DOI: 10.1111/mice.12447.

Zhao, H.S., Shi, J.P., Qi, X.J., Wang, X.G. and Jia, J.Y. (2017), "Pyramid scene parsing network", *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*", Honolulu, USA (CD-ROM).

Zhao, J., Mathieu, M. and LeCun, Y. (2016), "Energy-based generative adversarial network", *arXiv preprint arXiv:1609.03126.*

Zhao, X.F., Zhang, Y. and Wang, N.N. (2019), "Bolt loosening angle detection technology using deep learning", *Struct. Control. Health Monit.*, **26**(1), e2292. DOI: 10.1002/Stc.2292.

Zheng, S., Jayasumana, S., Romera-Paredes, B., Vineet, V., Su, Z.Z., Du, D.L., Huang, C. and Torr, P.H.S. (2015), "Conditional random fields as recurrent neural networks", *Proceedings of the IEEE International Conference on Computer Vision*, Santiago, Chile (CD-ROM).

Zhou, C., Chase, J.G. and Rodgers, G.W. (2019), "Degradation evaluation of lateral story stiffness using HLA-based deep learning networks", *Adv. Eng. Inform.*, **39**, 259-268. DOI: 10.1016/j.aei.2019.01.007.