Deep learning and civil engineering

Student

Zhili He

ID：191005

Instructor

Yao Yiming, Zhang Zhongwen, Qiao Ling,

Zhu Lei, Zhu Qian and Li Xing

Southeast University

止於至善

Research Paper Writing for Civil Engineering Term Paper

Title

Damage Detection and Structural Health Monitoring Using Deep Learning: A State-of-the-Art Review

Student

He Zhili,

ID: 191005

Instructor

Yao Yiming, Zhang Zhongwen, Qiao Ling,

Zhu Lei, Zhu Qian and Li Xing

School of Civil Engineering
Southeast University, Nanjing, China

July, 2020

Damage Detection and Structural Health Monitoring Using Deep Learning: A State-of-the-Art Review

Zhili He[1,2,*]

[1]*Key Laboratory of Concrete and Prestressed Concrete Structures of Ministry of Education, Southeast University, Nanjing 210096, P.R.China*
[2]*School of Civil Engineering, Southeast University, Nanjing 210096, P.R.China*

Abstract

With the development of computer software and hardware equipment, the progress of big data analysis technology and deep learning theory, deep learning technology has been widely concerned in all walks of life and has a subversive impact. Introducing deep learning techniques into traditional civil engineering tasks such as structural health monitoring and damage detection has also attracted more and more researchers' attention. Firstly, the connotation and research progress of machine learning, deep learning, structure monitoring and damage detection are systematically introduced. Then the development process of deep learning and the latest influential literature in the field of civil engineering based on deep learning are reviewed and the current research is classified. This paper classifies the research from the perspectives of one-dimensional data, two-dimensional data, three-dimensional data and intelligent detection equipment. The main research hotspots include structural response prediction, damage location, structural performance evaluation, health monitoring data cleaning, automatic detection and segmentation of structural apparent diseases, intelligent construction, 3D reconstruction of structures, point cloud data segmentation and intelligent detection equipment. Additionally, t several research directions with promising research prospects are posed and corresponding research plans and research methods are also put forward. This paper aims to provide reference for researchers in this field and promote the further development of related fields.

Keywords

Machine learning, Deep learning, Structural health monitoring, Damage detection

Correspondence:
Zhili He, School of Civil Engineering, Southeast University, Nanjing 210096, China.
Email: hzl@seu.edu.cn
Tel: +86-15151861213

Funding information:
None.

1. Introduction

Machine learning (ML) is an interdisciplinary subject involving probability theory, statistics, approximation theory, convex analysis, algorithm complexity theory and so on. ML focuses on how computers simulate or implement human learning behaviors in order to acquire new knowledge or skills and reorganize the existing knowledge structure to improve its performance. ML is the core of artificial intelligence and the fundamental way to make computers intelligent [1]. It enables computers to learn without explicit programming. Since it was put forward in the last century, ML has played an important role in science and engineering, finance and humanities, and has affected all aspects of people's life.

ML algorithm is divided into supervised learning and unsupervised learning [2]. Recently, weak supervised learning has been developed, which is a theory between supervised learning and unsupervised learning. Supervised learning uses the prior knowledge of labeled data sets to learn a function that is closest to the relationship between input and labeled output in data. The purpose of unsupervised learning is to infer the natural structure of a group of data points without target labels. Compared with supervised learning, unsupervised learning has the advantage that it does not need prior knowledge and avoids the complex process of data set building; however, its disadvantage is that it is difficult to learn effective results because of the lack of prior knowledge. Improving the learning effect of unsupervised learning is also one of the hot spots in current research. According to data characteristics (discrete or continuous) and task objectives, supervised learning can be further subdivided into classification and regression, while unsupervised learning includes clustering and dimensionality reduction [3]. Figure 1 summarizes two types of ML and some common and classic ml algorithms. In the next section, the latest algorithms proposed in machine learning will be introduced.

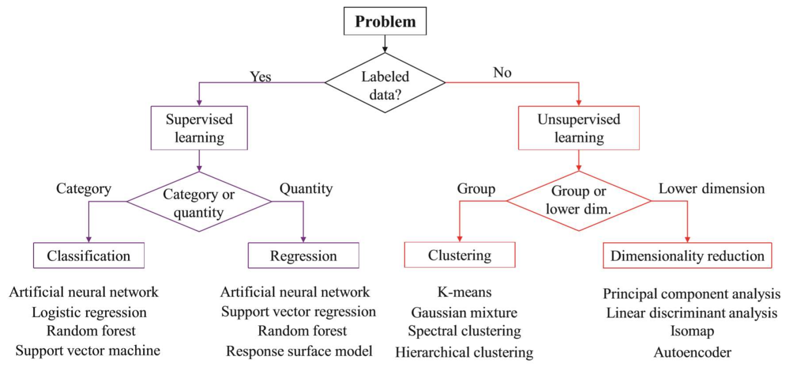


Fig. 1 Some commonly used and classical ML algorithms

The traditional machine learning algorithm has been widely used in civil engineering. As early as 2001, H. Adeli *et al.* [4] reviewed the integration of artificial neural networks (ANNs) and genetic algorithm (GA), wavelet analysis and fuzzy logic in civil and structural engineering. Adeli is currently a professor at Ohio State University, an academician of the Royal Spanish Academy of engineering, and a pioneer and outstanding scientist in the interdisciplinary field of civil engineering and computer science. He has made an influential, irreplaceable and pioneering contribution in the field of civil engineering and has shown extraordinary leadership in promoting the application of computer technology and information technology in many engineering fields around the world. At present, he is editor in chief of Computer Aided Civil and infrastructure engineering, ASCE, IEEE, aim and AAAs fellow. J. Zhang *et al*. [5] also based on pattern recognition technology, used structural vibration signals to identify deep-seated parameters of building structures. Then, in 2016, Amezquita Sanchez *et al.* [6] also reviewed the application of ANNs in civil infrastructure. It covers a variety of topics, including structural system identification, structural health monitoring, structural vibration control, structural design and optimization and prediction applications in the fields of construction engineering and geotechnical engineering. M. H. Rafiei and H. Adeli also used machine learning methods to explore the field of structural damage detection [7].

Recently, Xie *et al.* [3] comprehensively summarized and summarized the research and application of ML in the field of seismic engineering and extracted seven ml algorithms and four major subject areas that are most widely used in the field of seismic engineering. Seven ML algorithms include ANN, support vector machines (SVM), response surface model (RSM), logistic regression (LR), decision trees (DT) and random forest (RF). In addition, there are also hybrid methods combining various methods and some methods that are not so widely used, such as evolutionary computing (EC) and genetic expression programming (GEP). The four major subject areas are (1) seismic hazard analysis, (2) system identification and damage detection, (3) seismic fragility assessment and (4) structural control for earthquake limitation. In these four areas, the number of articles using different machine learning algorithms is shown in Figure 2. The larger the color circle in the figure, the more widely used.

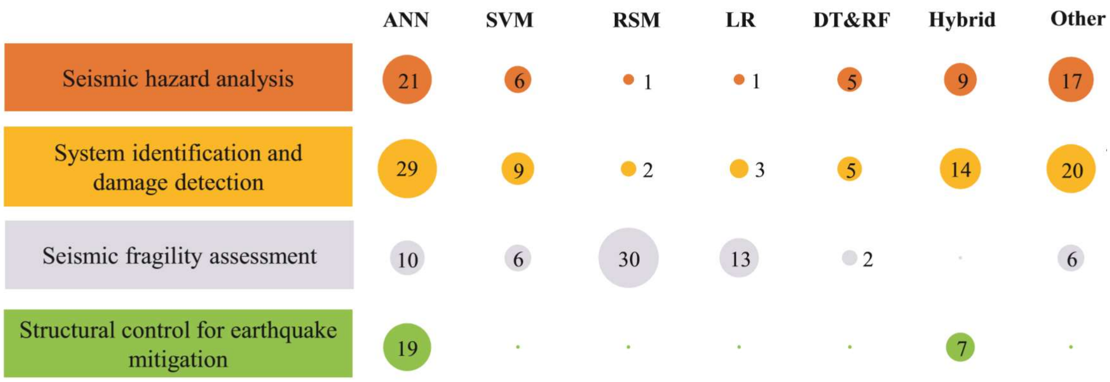


Fig. 2 Applications of seven classes of ML methods in four topic areas in seismic engineering [3]

Seismic hazard analysis includes the study of predicting the earthquake level and its associated uncertainties for a given site or location. The second theme is a dual field, in which system identification includes a series of studies that use ml to simulate structural systems and predict their deterministic seismic responses, while damage detection is widely defined as the use of ML models to identify, classify and evaluate seismic damage in civil structures. The third topic, seismic vulnerability assessment involving various sources of uncertainty, is a promising and popular area for practicing ml technology. The fourth theme is to equip ml with active and semi-active control structures to reduce the adverse effects of earthquake disasters. The application examples of ML algorithm in these four fields are shown in Figure 3.

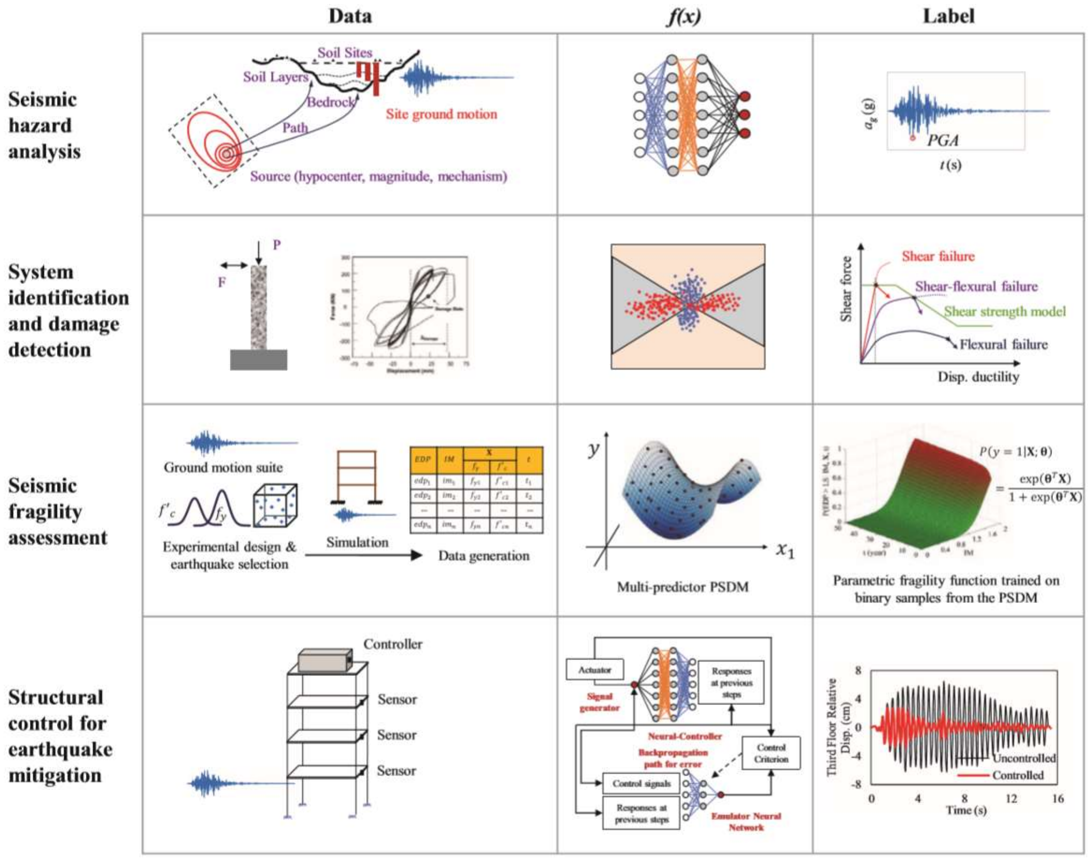


Fig. 3 Application examples of ML algorithm in these four topic areas [3]

Many researchers have applied ML method to predict the tensile, compressive and splitting strength of concrete members [8], [9]. In this research area, there are four most widely used ML methods: ANNs [10], SVM [11], DT and evolutionary algorithms (EA). Based on these algorithms, a number of model design schemes are proposed. These models can not only predict the strength, but also be used for sensitivity analysis, pointing out the influence weight of each input parameter on the concrete strength in the prediction process [13]. The process of predicting concrete strength based on machine learning method is as follows. Firstly, the model is trained based on a large number of test data, and then the predicted concrete strength is output based on the model with good training correlation through input parameters. The validation dataset provides an unbiased assessment of the fit between the model and the training data and prevents the model from over fitting by stopping the training process when the error increases. Some researchers combined the neural network with FRP reinforced concrete beam theory to estimate the shear bearing capacity of reinforced concrete beam [14].

Deep learning [15] is an important branch of machine learning. It is an important, transformative and subversive technology. However, when it comes to deep learning theory, it is not new to be exact. As early as

1986, the idea of deep learning was introduced into machine learning theory [16]. And it was used in ANN in 1999 [17]. However, it has not been widely used in the past, because the computing power of the computer at that time could not match the requirements of large-scale neural network computing. Therefore, the theory of deep learning remained on the surface and did not attract widespread attention. In recent years, with the development of computer hardware, the computing power is gradually improved, and the computing efficiency of CPU has been increased by geometric level. In addition, graphics processor unit (GPU) developed by NVIDIA and AMD can significantly accelerate the training speed of neural network, which makes it possible for deep learning to be widely used. In 2016, AlphaGo [18], the world's first go robot developed by the DeepMind team of Google, was born. In this most complex intelligence game field developed by human beings, it defeated Li Shishi, a world champion of go, by a score of 4:1. The event has aroused heated discussion all over the world, and the heuristic search, reinforcement learning and deep neural network behind it have attracted people's attention. Since then, many people have heard of a term for the first time, and they have studied deeply (include the author himself). Then, the updated AlphaGo master won the world's No. 1 player, Ke Jie, with a score of 3:0. In 2017, a further enhanced version of AlphaGo, AlphaGo Zero [19], was launched. Compared with the performance of the first generation AlphaGo robot, the score is 100:0. This series of actions can not help but remind people of the famous science fiction film terminator. Many people are also wondering whether artificial intelligence can replace human beings? (including the author himself). After these years of understanding, the author's understanding of deep learning has gradually deepened. Human beings still have a long way to go to realize the strong artificial intelligence which is introduced in science fiction movies. Compared with AlphaGo's go game itself, its far-reaching impact in human history is more significant. AlphaGo is undoubtedly a milestone in human history. AlphaGo brought "deep learning" into the eyes of the people of the world for the first time. It also inspired more people to join in the research of deep learning, and effectively promoted the development and progress of the field of deep learning.

Deep learning is a general term for a class of pattern analysis methods. It is an intelligent science that automatically learns and obtains knowledge from data. It mainly involves three kinds of methods: (1) Convolutional neural network (CNN). Neural network system based on convolution operation, namely CNN, which is the most widely used deep learning method. (2) Auto encoder neural network. In recent years, auto encoder neural network based on multi-layer neurons, including auto encoder and sparse coding, has attracted extensive attention in recent years. (3) Deep belief network (DBN). The neural network is firstly pre-trained by multi-layer auto encoder neural network, and the weights of neural network are further optimized by combining the identification information. Compared with the traditional ANN, the neural network based on deep learning idea often has a deeper structure, so it is usually called deep neural network (DNN). Through the multi-layer nonlinear neural network structure abstraction and processing features, the initial low-dimensional feature representation is gradually transformed into the high dimensional feature representation, and the complex regression, classification and other learning tasks can be completed with "simple model". It can be applied to supervised or unsupervised feature representation and pattern recognition. Therefore, deep learning can be understood as "feature learning" or "representation learning". In the specific implementation, the neural network structure is often designed through computer programming, and the complex data mapping relationship is learned with relatively simple network structure. At the beginning of the field development, researchers often have to implement the underlying code of neural network. In recent years, Caffe [20], Apache MXNet [21], Tensorflow [22] and Pytorch [23] and other neural network frameworks have provided a lot of convenience for relevant practitioners to design neural network models, conduct deep learning research or engineering applications based on deep learning.

At present, data-driven algorithm represented by deep learning has been widely used in various fields of production and life, and has been used by billions of people. It has a subversive impact on data mining, computer vision and natural language processing in the field of computer science, which also greatly promotes the development and progress of related interdisciplinary. Transformative solutions are introduced to different disciplines and directions. For example, medical and health [24], autonomous driving [25], astronomy [26] and material science [27], and even in the field of civil engineering infrastructure health monitoring and disease detection [28], [29]. In recent years, the combination with AI has become a hot and frontier research direction in the field of civil engineering. The development of ML and big data theory has also brought revolutionary changes to the development of SHM. Deep learning is also known as the fourth industrial revolution after steam technology, power technology, computer and information technology. In order to seize the commanding height of artificial intelligence, the investment all over the world is increasing rapidly in recent years, and colleges and universities have opened artificial intelligence major and related courses. Whoever masters AI will master the future. In recognition of the contributions of Yoshua Bengio, Yann LeCun and Geoffrey Hinton (the fathers of deep learning), they were awarded the A.M. Turing Award (the Nobel Prize in computer science) in 2019.

Structural damage is an inherent problem of engineering structures, which is usually defined as the change of system geometry or material characteristics, which has adverse effects on the performance, safety, reliability and service life of the structure [30], [31]. According to this definition, structural damage does not always indicate the complete failure of the system, but the relative deterioration of the system function leads to the decline of structural performance [32]. However, if remedial measures are not taken, damage may accumulate until a critical state is reached. Sudden failure of structural system may occur, which will damage people's life and property safety [33]. During the service period, civil engineering structure will be affected by various man-made environment and natural environment, which will lead to a variety of damage. And once the damage occurs, it is very easy to accumulate and spread. These factors will also lead to the continuous degradation of structural performance and shorten the service life of the structure [34]. For example, the creep, shrinkage and fatigue of the structure itself during the service period will corrode under the influence of external environment and will be damaged by extreme conditions such as typhoon and earthquake [35]. These all affect the health status of civil engineering infrastructure to varying degrees. If not detected, warned and maintained in advance, it is very easy to cause irreversible damage to the structure within the design service life [36]. For example, the corrosion or fatigue of steel bridge suspender leads to the sudden fracture of suspender, which leads to the overall collapse of the bridge. On October 1, 2019, a sea-crossing bridge in Taiwan, China, collapsed for this reason. Six people were killed and twelve others injured. Therefore, it is very important to carry out reasonable and normal detection of infrastructure, evaluate the health status of structures, and provide early warning for structural damage. Many researchers have also conducted a lot of research in this area [29], [37].

At present, structural damage monitoring mainly includes two categories: Structural Health Monitoring (SHM) and Structural Damage Detection (SDD). SHM usually locates and evaluates structural damage based on structural response recorded by relevant equipment and makes judgment and decision on structural health status [38].

SHM is an extensive and highly interdisciplinary research field, involving long-term measurement of environmental and operating conditions, data acquisition and management, parameter and system identification and other aspects. [39]. SHM system has been widely used in mechanical engineering, aerospace, civil engineering and other fields [40]. The most successful and mature damage detection system is used in mechanical engineering to detect the vibration state of mechanical parts [41]. This system uses the vibration response recorded by the machine in terms of displacement, speed or acceleration to evaluate the safe state of its bearings and gears [42]. However, the vibration response of machinery is little affected by manual operation and environmental conditions, which means that any significant difference in vibration characteristics of the system can be attributed to some type of damage. Since the type and location of mechanical damage are clearly defined, it is very feasible to associate each change of vibration characteristics with a specific damage type and location [43]. Recently, in the field of mechanical engineering, many researchers have applied artificial intelligence and deep learning technology to mechanical health monitoring [44], [45]. Zhang *et al.* [46] proposed a convolutional neural network model to study bearing fault diagnosis under noise environment and different working loads, while Ince *et al.* [47] applied convolutional neural network to detect motor fault. The success of vibration based mechanical condition monitoring has prompted researchers to implement similar techniques in SHM of civil infrastructure. However, in the field of civil engineering, the types of structural damage and the mechanism of damage on structural safety are very complex, and the structure is greatly affected by the external environment, so the structural health monitoring in the field of civil engineering is a greater challenge. A typical SHM system consists of software and hardware, as shown in Figure 4. The hardware part is composed of sensors and data acquisition interfaces for measuring and collecting data, usually including accelerometer, speedometer, strain gauge, weighing sensor or optical fiber sensor and data acquisition module [48]. The software component of the damage detection system is a signal processing and pattern recognition algorithm library, which is used to convert the signal obtained by the sensor interface into the basic information reflecting the condition of the monitored structure [49]. Disease detection algorithm is the core of SHM system. An excellent disease detection algorithm needs to be able to automatically judge whether the damage exists, locate the damage location and evaluate or quantify the damage severity from the whole system, so as to evaluate the overall performance of the structure. A large number of researchers have also carried out extensive exploration and research in this field [28]. Recently, many scholars have proposed to apply deep learning to the field of structural engineering monitoring. The specific work will be introduced in Section 3 of this paper.

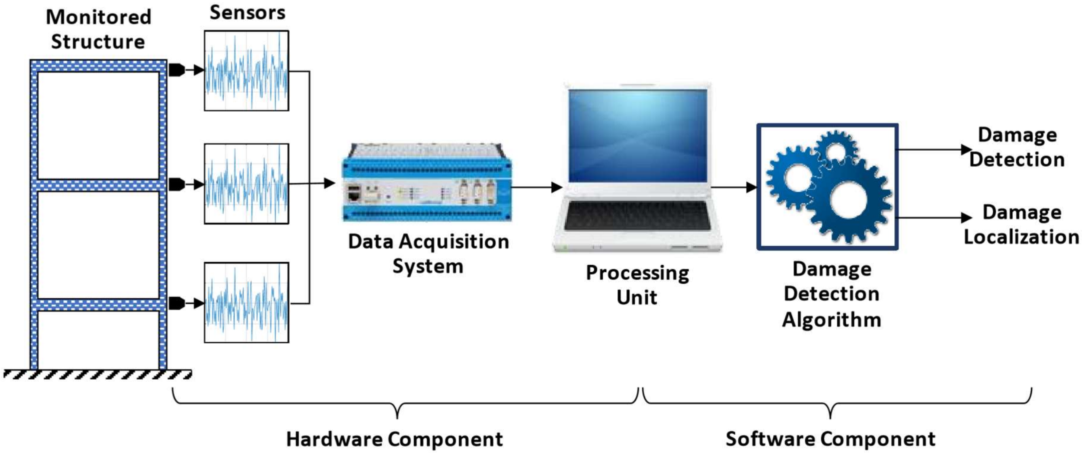


Fig. 4 Main components of SHM systems

However, SDD can be directly located and quantified by contact or non-contact detection by manual method [50]. The traditional damage diagnosis method of civil structure is mainly based on artificial visual inspection. This traditional detection method has many disadvantages [36]. (1) There are many blind spots in patrol inspection. Due to the complex structure of long-span bridges, it is difficult to effectively inspect many areas manually, and there are many blind areas in detection. For example, the joint of concrete structure, the outer surface of cable tower, deep water foundation, the bottom of main beam in canyon area. (2) The cost of manpower and equipment is high. Traditional methods need to use scaffolding, inspection vehicle equipment, the size of the civil structure is relatively large, regular inspection also costs a lot of manpower and material resources. Taking the traditional inspection vehicle method as an example, the fixed equipment cost is 15000 yuan / km, the labor cost is 6700 yuan / km, the equipment rental cost is 42000 yuan / km, the equipment loss cost is 007300 yuan / km, other direct costs are 2000 yuan / km, the related indirect costs are 1500 yuan / km, and the total economic cost is as high as 52300 yuan / km. (3) Low intelligence, low detection efficiency and low precision [51]. Manual detection mainly depends on human resources, and the degree of intelligence is very low, and the detection efficiency is difficult to meet the needs. The accuracy of traditional detection tools is insufficient. Traditional detection methods mainly use tape measure, total station, micrometer and other commonly used test instruments to measure the measured items. The measurement accuracy can only reach millimeter level, and the measurement accuracy is low. Moreover, manual detection has certain randomness and uncertainty, which depends on the subjective judgment of human, so the detection effect is difficult to guarantee.

(4) High security risk. There is a high safety risk for the detection personnel to carry out outdoor work in the traditional way. For example, if the personnel take the hanging basket to work at height to detect the cable, a little carelessness will lead to safety accidents. Figure 5 below shows the diagram of manual detection.

(a)

(b)

(c)

(d)

Fig. 5 Manual detection. (a) Bridge inspection vehicle; (b) Detection of bridge bottom damage; (c) Crack detection; (d) Cable detection.

At present, a variety of non-contact methods are also applied to the disease detection of infrastructure, such as 3D scanning, industrial camera and microwave radar. Also developed a variety of advanced equipment, such as cable robots, unmanned aerial vehicle (UAV) and other equipment for infrastructure disease detection. The figure below shows three-dimensional scanning equipment, optical measurement method, microwave radar method and UAV to detect the dynamic and static deformation, cable force and apparent disease of bridge structure. (Some of the pictures were taken in the experiment participated by the author in June this year.) In addition to the use of advanced equipment, people have also proposed many new methods suitable for structural detection based on advanced algorithms such as artificial intelligence and big data analysis [29], which have achieved good engineering application results and have a wide range of application prospects. It is hoped that these advanced intelligent technologies and methods will be mature as soon as possible, and large-scale engineering applications will be carried out to liberate human productivity and protect structural health! Professor Zhang Jian's team of Southeast University of China has carried out extensive research in the field of non-contact intelligent structural detection, and has made a series of progress, including artificial intelligence algorithm for crack detection [52], [53], UAV real-time disease detection [54], non-contact cable force measurement based on UAV and computer vision [55], cable force estimation of long-span cable-stayed bridge and suspension bridge based on microwave radar [56]. The specific technology and research progress in this field will be discussed in sections 4, 5 and 6 of this paper.

(a)

(b)

(c)

(d)

Fig. 6 Non-contact equipment. (a) Microwave radar; (b) Industrial camera; (c) UAV system; (d) 3D laser scanning equipment.

This paper reviews the frontier research (DL based), which has made great innovation and contribution in the field of SDD and SHM in recent years.

In order to highlight the logic, the content is divided into three parts. They are one-dimensional data research, two-dimensional data research and three-dimensional data research. One dimensional data is mainly based on sensor signal structural health research, two-dimensional data is mainly based on image data disease detection, three-dimensional data is mainly based on three-dimensional scanning point cloud data for digital twin related research, such as structural modeling and finite element analysis.

The specific content of this paper is arranged as follows. Section 2 reviews the development of deep learning technology in the field of computer science, which is the core driving force of the current cross direction with civil engineering. Only by understanding and following the development of the original field can we carry out interdisciplinary research better. Section 3 introduces the latest development of deep learning in the field of structural health monitoring (1D data). In Section 4, the research of disease recognition based on deep learning is described in detail. Compared with one-dimensional sensor data, disease detection is related to computer vision. Computer vision is one of the two development directions of deep learning (computer vision and natural language processing), so disease detection has attracted more and more attention. Section 5 discusses the related research in the field of 3D data. Compared with the previous two fields, this field is more novel and difficult, and the current research is relatively less. The research progress of intelligent detection equipment in the field of structural inspection is reviewed in Section 6. In Section 7, some potential and valuable directions in the interdisciplinary field of civil engineering and deep learning are briefly discussed. In Section 8, The research gaps mentioned above are prospected and the corresponding research plans are put forward from the author's personal point of view. Finally, Section 9 is provided to list the prospects as the big picture and highlights the main points of the paper.

2. Deep learning

2.1 Brief introduction

The theory of deep learning was put forward in the second half of the 20th century and has been developed and perfected continuously. It has expanded the scope of machine learning and now it has become an important part of ML. In addition to the supervised and unsupervised methods introduced in the first section, ML algorithms can also be divided based on algorithm characteristics. It can be divided into clustering, Bayesian, Regression, Instance Based, Neural Networks (NN), DT, Ensemble Learning, Dimensionality Reduction and Deep Learning. The specific classification is shown in the figure below.

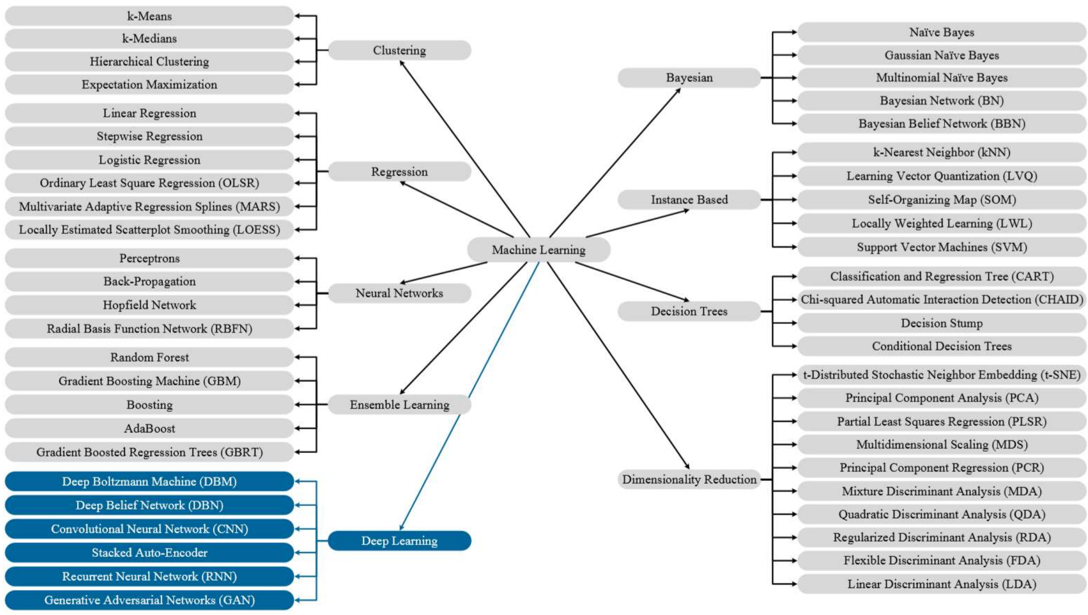
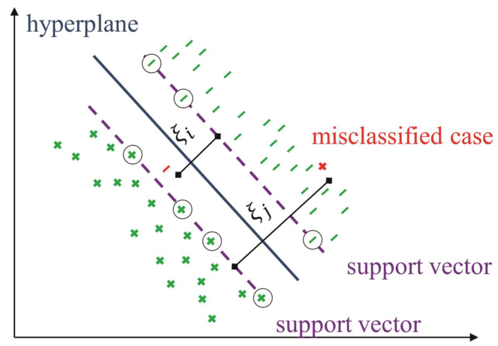


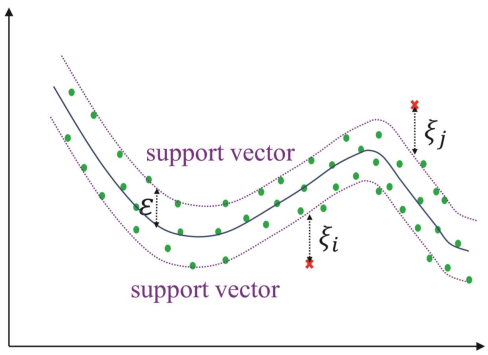
Fig. 7 ML algorithms mind map [29]

Deep learning promotes the great progress of modern computer science and has made great progress in solving long-term problems in computer vision, natural language processing, speech recognition and robot technology. At the same time, it also replaces the traditional machine learning algorithm in many fields. Before deep learning, one of the most widely used algorithms in classification and regression is SVM [57].

SVM is a binary classification algorithm, which uses kernel function to implicitly map data to high-dimensional feature space. For the separable data shown in Figure 8 (a), an optimal edge classifier is performed to construct a separation hyperplane that maximizes the edge between the hyperplane and the support vector, which includes the data points closest to the hyperplane. In addition to data classification, support vector machine can also be used as a regression method [58]. For the ε - insensitive region, the error is regarded as 0. As shown in Figure 8 (b), through nonlinear kernel mapping, SVM performs linear regression in high-dimensional feature space and adds relaxation variable to measure the deviation of training samples outside the ε-insensitive region [59].



(a)



(b)

Fig. 8 SVM. (a) Classification; (b) Regression.

After the rise of deep learning, the popularity of SVM research has gradually declined. Deep learning technology has stronger nonlinear fitting ability, which makes it achieve satisfactory results in data classification and regression of many traditional machine learning tasks. Deep neural network gradually replaces SVM.

Articles published in the field of computer science are mainly published at top conferences. The type A conferences specified by China Computer Federation (CCF) include IEEE Conference on Computer Vision and Pattern Recognition (CVPR), International Conference on Computer Vision (ICCV), European Conference on Computer Vision (ECCV), AAAI Conference on Artificial Intelligence (AAAI), International Joint Conference on Artificial Intelligence (IJCAI), Conference and Workshop on Neural Information Processing Systems (NeurIPS), International Conference on Learning Representations (ICLR) and other famous conference. Before deep learning, these conferences were occupied by various machine learning algorithms and traditional methods. Since deep learning has become a hot research topic, papers at these top conferences are basically about deep learning, and the number of contributions has witnessed an explosive growth in the past two years. In June 2020, the number of contributions to CVPR 2020 exceeded 6000, while that of AAAI 2020 even exceeded 8000. Figure 9 shows the number of contributions to CVPR over the years, and Figure 10 shows the number of contributions to AAAI over the years. From about 2015, the number of contributions began to show a blowout growth, which is also a hot time point for deep learning. The rapid growth of the number of contributions directly reflects the popularity of this field, which has attracted the attention of researchers from all over the world.

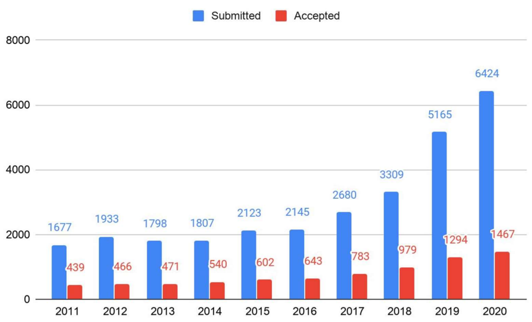


Fig. 9 CPVR contributions over the years

Fig. 10 AAAI contributions over the years

Directly related to the number of contributions, the citations of excellent work have increased rapidly. For example, in CVPR in 2016, Kaiming He proposed the deep residual network (ResNet) [60]. This unique residual network structure design effectively solved the problem that neural network will degenerate with the deepening of network depth, which made it difficult to effectively train. This work makes deep neural networks possible. Therefore, as a backbone network, it has been introduced into a large number of follow-up studies. The following figure shows the most important shortcut design in ResNet. By July 2020, the number of citations has reached 26776! (Data Source: Research Gate). It is hard to imagine in other fields, such as civil engineering.

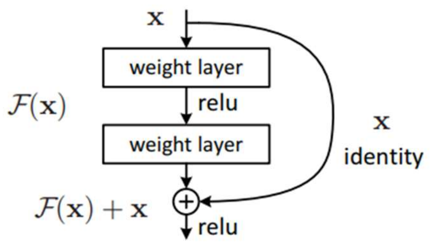


Fig. 11 Residual learning: shortcut

Computer vision technology is to introduce deep learning into image recognition and processing tasks and use deep learning technology to model image processing. Computer vision technology uses deep learning to identify and interpret images. Just like the visual reasoning process of human vision, computer vision technology can distinguish objects, classify them, and sort them according to their size. It takes images as input and provides output in the form of size, color intensity and other information.

At present, computer vision tasks mainly include Classification, Object Detection, Semantic Segmentation, Instance Segmentation, Pose Estimation, Enhancement and Restoration and Action Recognition. The following is a brief introduction to some classic neural networks in computer vision field.

2.2 Two-dimensional data

At present, CNN is widely used. This is a multi-layer network learning algorithm, which has the ability of representation learning. It extracts the compressed image features through continuous convolution and other operations, and finally forms a relatively high-level feature. According to its hierarchical structure, the input information is classified by translation invariant. Its basic components are convolution layer, pooling layer and full connection layer.

In 2012, Krizhevsky *et al.* Designed AlexNet [61] and successfully used ReLU as the nonlinear activation function of CNN. They also used dropout operation to ignore some neurons to effectively avoid over fitting of the model. The average pooling operation was abandoned and the maximum pooling operation was widely used. Alexnet's many innovative attempts provide valuable experience for the subsequent CNN model design, and the operations such as rule and maximum pooling are also widely used. It won the championship in ImageNet large scale image recognition challenge (ILSVRC) in 2012, with test error of 16.4%, which is much lower than that of using traditional method. After that, CNN has attracted more and more researchers' attention in the field of computer vision and has been widely used. The following figure shows the network structure of AlexNet.

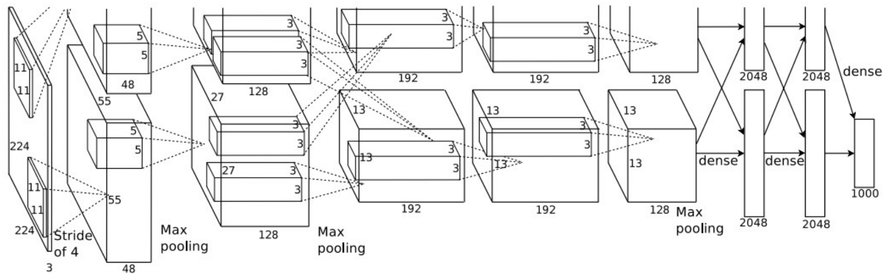


Fig.12 The architecture of AlexNet

In 2014, the InceptionNet (also known as GoogleNet) proposed by Google company adopted decomposition convolution and used average pooling layers to replace the full connection layers, which improved the network performance. The improvements controlled the calculation amount and ensured the calculation efficiency. The network won first place in the ILSVRC, reducing the Top-5 error rate to 6.67%. The biggest innovation of inception net is the multi branch network design idea, which can learn a lot of characteristics. In this network, the batch normalization operation is first used, which can (1) improve the training speed and network convergence, (2) improve the generalization ability of the model to prevent over fitting. The branch module of the network is shown in the figure below.

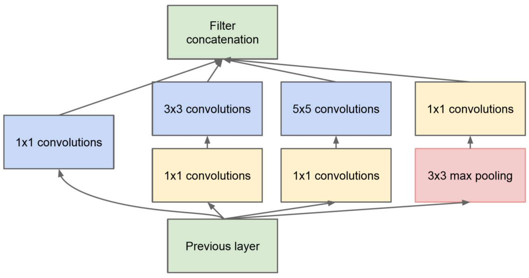


Fig. 13 Inception module

VGG network [63] which was the same period as the InceptionNet pointed out that the depth of the network is the key part of the excellent performance of the algorithm, reducing the Top-5 error rate to 7.3%, which won the second place. VGG is also a very classic convolutional neural network design. Firstly, modular design is proposed, which divides the network into macro structure (network includes different stages) and microstructure (block design). This is a creative and still widely used design ideas today, which can effectively simplify the network design ideas.

Subsequent studies found that the simple accumulation of network depth may lead to a series of problems, such as the disappearance of gradient, the decrease of model accuracy, and the degradation of model. In 2015, ResNet [60] (deep residual network) introduced jump connection to directly learn the residual of the network and filter the redundant information of the network. In the process of back propagation, the additive part can reduce the gradient to a certain extent and disappear; it won the first place of ILSVRC in 2015. The average error rate is only 3.57%, while that of human eyes is 5.1%. This is the first algorithm to surpass the recognition accuracy of human eyes in this competition. In addition, its recognition speed is much faster than that of human eyes. Since then, ResNeXt [64], DenseNet [65] and other networks have been proposed on the basis of ResNet. DenseNet has the same basic idea as ResNet, but it establishes dense connections between all layers and subsequent layers to realize feature reuse. It can achieve better performance than ResNet with less parameters and calculation costs, and won the best paper award of CVPR 2017. The figure below shows a five layer dense block design.

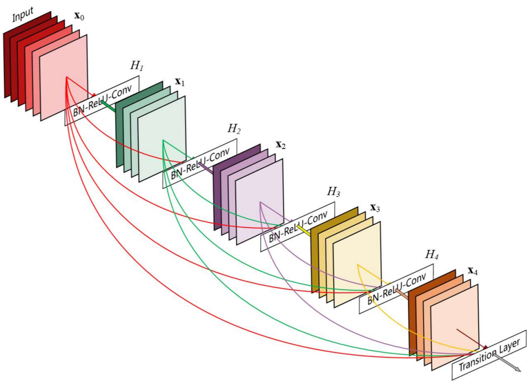


Fig. 14 A 5-layer dense block

In 2017, SENet [66] adopted the consideration of the relationship between feature channels, introduced attention mechanism into feature channels through the

Squeeze and Excitation modules. SENet directly learned the importance factors of each feature channel which could promote the useful features and suppress the useless features r. The network won the first place in the ILSVRC that year, reducing the top-5 error rate to 2.251%.
Squeeze operation

$$z_c = F_{sq}(u_c) = \frac{1}{H \times W}\sum_{i=1}^{H}\sum_{i=1}^{H} u_c(i,j) \quad (1)$$

Excitation operation

$$\begin{aligned} \mathrm{s} &= F_{ex}(z, Wp) = \sigma\big(g(z, Wp)\big) \\ &= \sigma\big(W_2 ReLU(W_1 z)\big) \end{aligned} \quad (2)$$

Where W and H are the width and height dimensions, u_c is the characteristic matrix, z is the full connection layer, Wp is the super parameter, W_1 is the scaling factor and W_2 is also a full connection layer. The figure below shows the schematic diagram of Squeeze and Excitation modules.

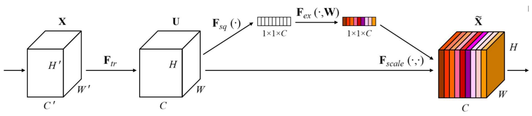


Fig. 15 A Squeeze-and-Excitation block

operation. Then multiple spaces were assigned by multiple Head operation. In the end, self-attention mechanism was realized by point multiplication operation. In 2020, Zhang hang, who is a 2013 alumnus of Southeast University and a young scientist of Amazon, proposed ResNeSt: Split-Attention Network [70]. As a backbone network, the network achieves SOTA results in many tasks such as image classification, object detection, instance segmentation and semantic segmentation. The split attention network is shown in the figure below.

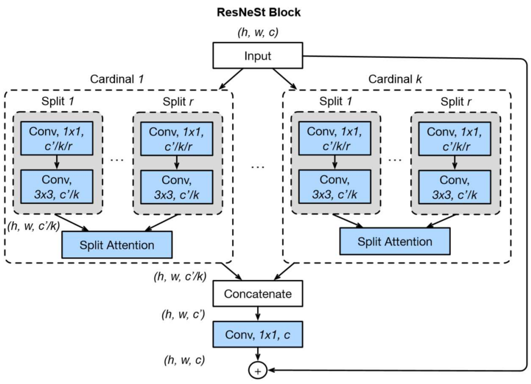


Fig. 16 ResNeSt block

Attention mechanism was first widely used in the field of natural language processing. Since senet, attention mechanism has been applied to CV field, and has become a very popular research direction in recent years. SangHyun *et al.* [67] proposed CBAM by combining the attention mechanism of feature channel and feature space. Compared with SENet, CBAM adds a feature extraction method of maximum pooling, which takes the extracted features of channel attention as the input of spatial attention module. Later, Gao *et al.* [68] proposed GSoP-Net, Bello *et al.* [69] proposed AANet, and introduced additional feature mapping by using the attention mechanism that could jointly participate in space and feature subspace. Firstly, the attention weight graph was obtained by matrix

Some classic backbone networks that have achieved good results in a variety of computer vision tasks are mainly introduced above. Backbone networks are also the basis of other CNNs. Many private networks that have achieved results in different tasks which have learned from backbone networks to varying degrees. Here's a brief summary of some of the most classic tasks in different computer vision tasks.

At present, there are two main development directions of target detection based on deep learning: two stage target detection algorithm and one stage target detection algorithm. The idea of the former is to generate a series of candidate frames (positive / negative samples) by the algorithm, and then classify the samples by CNN. The latter does not use the idea of generating candidate frames but locates the target by return. The former is superior in detection accuracy and positioning accuracy, while the latter is superior in algorithm speed. In 2014, Ross B. Girshick *et al.* [71] proposed the R-CNN algorithm, and R-CNN algorithm adopted selective search to generate candidate boxes of positive and negative samples and input the boxes into the structure of CNN. The features of positive and negative samples are extracted by CNN and the corresponding feature vectors are formed. Finally, A SVM is designed to classify the feature vectors, and the target coordinates and category information are obtained by regression of candidate boxes. Compared with the traditional target detection algorithm, R-CNN achieves 50% performance improvement. In 2015, Ross B. Girshick *et al.* proposed an improved Fast R-CNN algorithm [72], which used ROI pooling as a new pooling layer to pool the feature map of candidate box region. Fast R-CNN effectively overcomes the shortcoming of fixed input image size of R-CNN. In 2015, Ren *et al.* [73] proposed Faster R-CNN algorithm and designed a full convolution sub network RPN (Region Proposal Networks) to generate candidate boxes. The algorithm flow mainly consists of two stages. Firstly, the feature map is generated by the backbone network, and then a series of candidate frames are generated through the RPN. Then, the preliminary regression of coordinates and the classification of the front / background are performed, next the R-CNN is used as the head network to further refine the classifies of the candidate boxes generated in the previous step and coordinates regression. The whole process shares the feature map information extracted from the backbone network, saving the display memory. The figure below shows the structure of Faster R-CNN network.

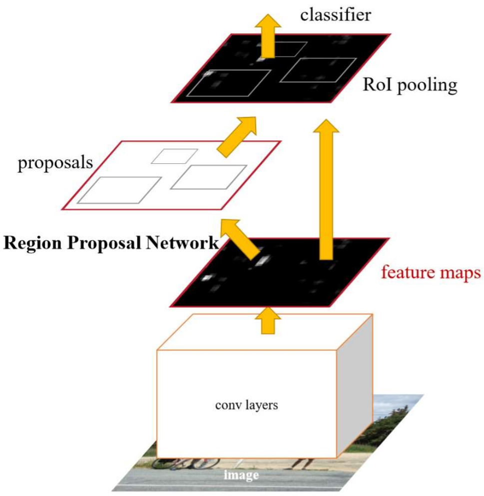


Fig. 17 Faster R-CNN

In 2015, Joseph Redmon *et al.* [74] proposed one stage method based on regression: Yolo (You only look once) algorithm, which is based on the global information of the image, divides the image into 7 × 7 grid windows, extracts feature training through convolution network, and predicts the coordinate information and various confidence levels of the inner border of each grid. The activation function is PRelu, and the speed can reach 45fps. The disadvantage is that the positioning is not accurate and the detection effect of small objects is poor.

In 2016, Wei Liu *et al.* [75] proposed SSD algorithm to improve the positioning accuracy of Yolo algorithm. SSD combines the idea of direct regression coordinates and category information in Yolo and the idea of Fast R-CNN 's anchor mechanism to generate suitable candidate frames. Results are predicted on convolution layer charts at different scales. The output predicted border coordinate is a multiscale result because it uses local features of different scales to perform border regression at different locations on the entire image. On the one hand, it maintains the real-time performance of YOLO algorithm, on the other hand, it also satisfies certain border positioning effect. The disadvantage is that it is difficult to detect small targets. After that, there have been different improvements in the SSD network and Yolo network. For example, the authors of Yolo network launched YOLOv2network in 2016 [76] and YOLOv3network in 2018 [77]. YOLOv4 network were proposed in 2020. Each version of Yolo network is highly praised for its high efficiency and high precision, and has been widely used in industry. The figure below shows the comparison between YOLOv4 network and other mainstream networks.

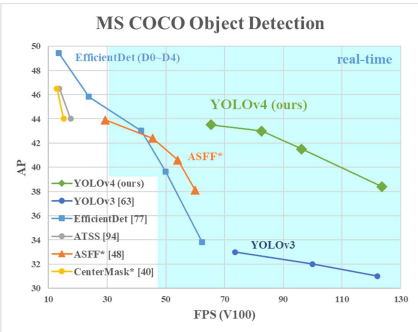


Fig. 18 Comparison of YOLOv4 and other state-of-the-art object detectors

In the field of semantic segmentation, Shelhamer *et al.* [79] proposed Fully Convolutional Network (FCN) in 2015, which is a pioneering work for semantic segmentation based on deep learning. The FCN network converts the full connection layer of a traditional CNN into a convolution layer, so it is named Fully Convolutional Network. The network allows the input of any size of image and has better applicability. Based on the FCN network framework, Ronneberger *et al.* [80] proposed U-NET. Because the network structure is similar to the capital letter "U", it is named U-NET. Unlike FCN, U-NET uses feature fusion based on stitching to improve channel depths. At present, U-NET is widely used in the field of medical image processing. The following is a schematic diagram of the architecture of U-NET.

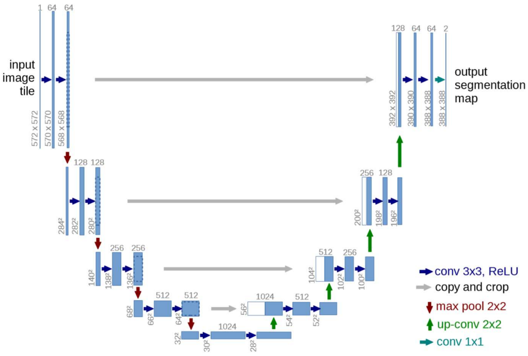


Fig. 19 U-NET architecture

In 2017, Kaiming He *et al.* [81] proposed the Mask R-CNN algorithm, using ROI Align to replace the ROI pooling in the Faster R-CNN. The network extends the R-CNN header, adds a semantic segmentation branch: FCN layer (Mask layer) to predict the masks of the targets, and finally realizes the pixel level semantic segmentation. This network has a clear idea and excellent effect. Since it was proposed, it has become a benchmark algorithm in the field of semantic segmentation. The following algorithms are inevitably compared with it.The network structure of Mask R-CNN is shown in the figure below.

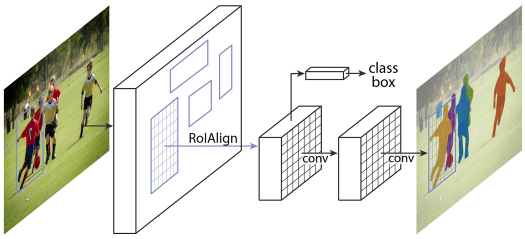


Fig. 20 The Mask R-CNN framework

In Figure 18, a classical network to be compared is called EfficientDet [82]. This network is a SOTA network proposed by Google research team in 2019. It obtains optimal results on almost all data sets, and has high computational efficiency. EfficientDet takes the former SOTA network EfficientNet [83] as the backbone network, uses BiFPN as the feature network, and uses the shared bounding boxes / category prediction results. The recognition effect of the network is far better than that of the mainstream networks such as Mask R-CNN, RetinaNet and and YOLOv3. The figure below shows the comparison results of EfficientDet and different networks. It should be noted here that since a network is often capable of multiple computer vision tasks, the following figure compares YOLOv3 and Mask R-CNN at the same time.

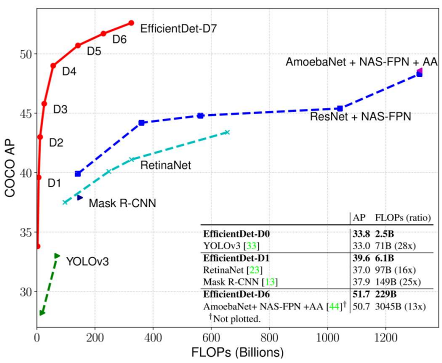


Fig. 21 comparison results of different networks

2.3 One-dimensional data

Previous research in the field of deep learning is more based on convolutional neural network. Recently, the discovery of hidden laws based on data-driven method has attracted more and more attention. People use modern machine learning technology, especially deep neural network, to model and restore partial differential equations and ordinary differential equations and have made a series of progress [84]-[87]. For example, a new type of physical information neural networks (PINNs) [88] has been widely studied recently.

Based on the automatic differential algorithm, the physical information constraints are embedded in the neural network, which can effectively model and PINNs the well posed partial differential equations and ordinary differential equations, such as Burgers' equation and Allen Cahn equation. Maziar Raissi *et al.* [89], [90] also used PINNs to solve the inverse problem of the model, and achieved very good results, such as Kortewegde Vries Equation. In addition, he also coded Navier-Stokes equations into neural network, which can effectively carry out fluid dynamics modeling [91].

Many researchers have studied the application of PINNs in other fields. Based on PINNs, Ehsan Haghighat *et al.* [92] established a model for mechanical solution and discovery of linear elastic solid. M. Torabi Rad *et al.* [93] applied PINNs to the study of alloy solidification benchmark. Although PINNs has been successfully applied in many fields, the theoretical research on its convergence is still in its infancy. Yeonjong Shin *et al.* [94] proved that it can strongly converge to the theoretical solution of PDE based on Schuader approach, which is the first show the consistency of the PINNs methodology, laying the theoretical foundation of PINNs.

Figure 22 below shows the forward problem solving of Burgers equation. It can be seen that PINNs method can obtain very high accuracy. Figure 23 below shows the network structure suitable for solving linear elastic solid mechanical solutions.

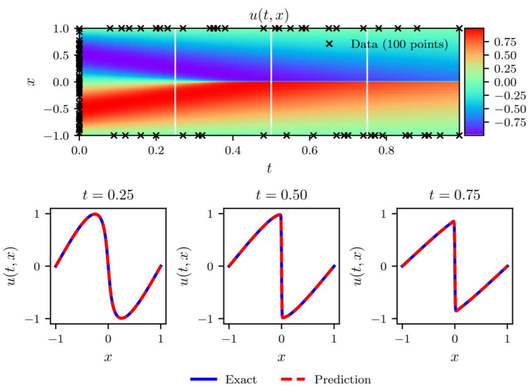


Fig. 22 The solution of Burgers equation[88]

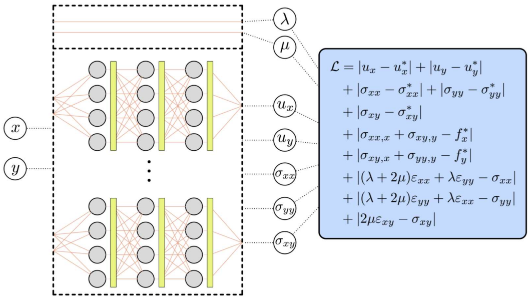


Fig. 23 Network architecture[93]

2.4 Three-dimensional data

With the development of three-dimensional scanning equipment such as lidar, the importance of 3D data has gradually increased, and it has many applications in automatic driving, Simultaneous Localization and Mapping (SLAM) and other fields.

Recently, deep learning methods for processing 3D data have been widely concerned. Three dimensional deep learning includes three types: multi perspective, voxel and point cloud. Multi view is the combination of two-dimensional images from multiple perspectives into a three-dimensional object. Voxel is the representation of the object as the voxel in space for three-dimensional convolution similar to two-dimensional. Point cloud is to directly import the three-dimensional point cloud data into the three-dimensional convolution network for processing.

Based on the auto encoder structure, Wu *et al.* [95] of Oxford University proposed a method for learning 3D deformable object categories from original single view images without external supervision. The 3D shape of an object can be reconstructed from a single image without supervision. This paper won the CVPR 2020 best paper award. Chen *et al.* [96] proposed an unsupervised method to generate compact structured polygonal meshes for 3D data segmentation and reconstruction. The results of segmentation and reconstruction are compared with other methods as shown in the figure below. This paper also won the CVPR 2020 best student paper award. Three-dimensional data processing, segmentation and reconstruction is a very promising direction, which is expected to get more attention in the future.

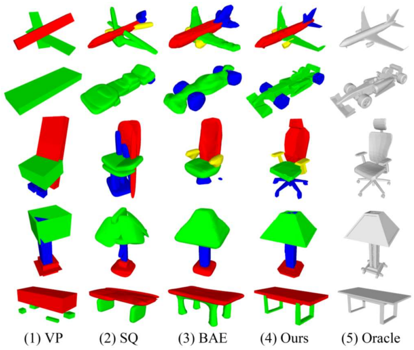


Fig. 24 Segmentation and reconstruction/Qualitative

Point cloud data has two characteristics: disorder and rotation, that is, the order of points does not affect the representation of the overall shape in space, and the coordinates of the same point cloud will change after rigid body changes in space. Because of the huge amount of data in point cloud, it is much more difficult to process 3D data than 2D data.

Until the end of 2016, Qi *et al.* [97] of Stanford University proposed the first deep learning framework PointNet for point cloud data classification and segmentation. PointNet solves the problem of rotation through spatial transformation network, solves the disorder problem by max pooling, and extracts the overall features. The basic idea is to learn the corresponding spatial code of each point in the input point cloud, and then use the characteristics of all points to get a global point cloud feature. The research paper was published at the CVPR 2017.

Subsequently, the author proposed PointNet++ [98], because PointNet can't capture the local structure problems caused by metric space, which limits the network's ability to recognize fine scenes and generalize complex scenes. In addition, the point cloud is uniformly sampled, but the density of the point cloud data in the actual scene is often different. PointNet++ pays more attention to the processing of local structure features, and considers different density of point cloud data, which improves the recognition accuracy. The work was presented at the NeurIPS in 2017. So far, more and more researchers pay attention to the processing of 3D point cloud data. The network structure of PointNet++ is shown in the figure below.

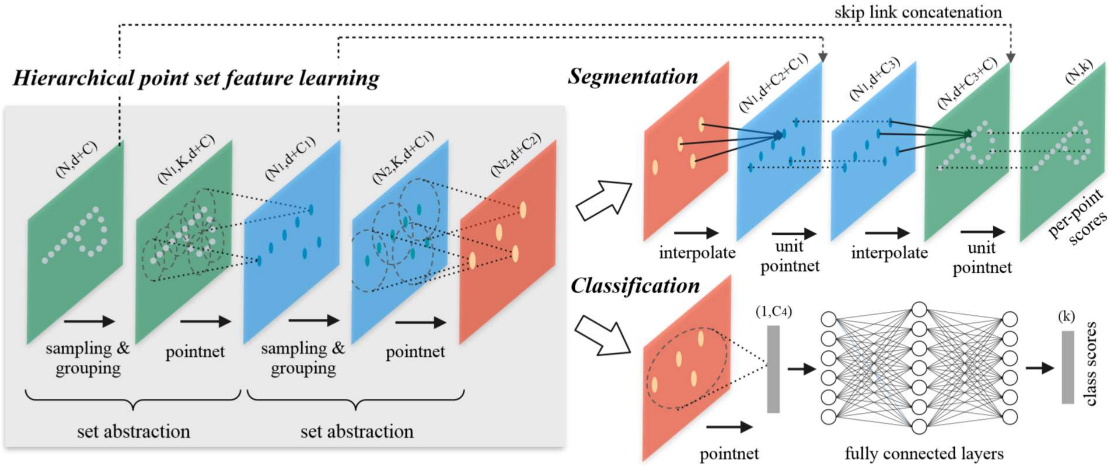


Fig. 25 architecture of PointNet++

In recent two years, Ben-Shabat *et al.* [99] proposed an unstructured 3D point cloud normal estimation method based on convolution neural network, which can be used for surface reconstruction, etc. The diagram below shows the network structure. The work was presented at the CVPR in 2019. Komarichev *et al.* [100] proposed circular convolution neural network to process 3D point cloud data. This new convolution operator can capture the local domain characteristics of point cloud and obtain high accuracy in large-scale scene segmentation. In addition, many researchers based on Graph Neural Network (GNN, generally using Graph Convolution Network, GCN) [101] for point cloud data learning and also achieved good results.

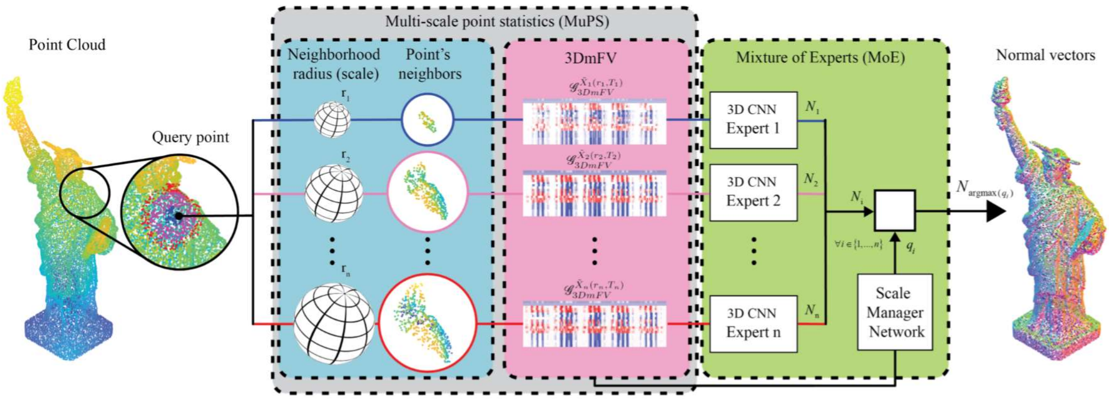


Fig. 26 Nesti-Net architecture for normal estimation

2.5 Software Frameworks

At present, researchers do research and application of deep learning, rarely write the underlying code themselves, more based on the framework of deep learning. The earliest deep learning framework was Theano, which was developed as a compiler for CPU and GPU in Python, rather than a deep learning framework at first. After 2017, Theano stopped updating and faded out of human vision, but it inspired the development of the follow-up frameworks and laid a foundation for them.

The mainstream deep learning framework includes Caffe written by Dr. Jia Yangqing of University of California, Berkeley and subsequent versions of Caffe2 [20]. This is also one of the early deep learning frameworks. Jia has an undergraduate and master's degree from Tsinghua University and a Ph.D from the University of California, Berkeley. In 2019, Dr. Jia Yangqing returned to China as vice president of Alibaba technology. Apache MXNet framework developed by Amazon Group [21]. The framework was developed by Chen Tianqi and Li Mu, both of whom graduated from Shanghai Jiaotong University. Google launched TensorFlow [22] and keras framework [102] in 2015. Facebook released PyTorch framework [23] in 2017. It is worth noting that Dr. Jia Yangqing is also the main R & D personnel of the framework.

At present, PyTorch framework is widely used by researchers. Because of its clear and simple coding ideas, easy debugging and reasonable API, it is more and more popular. However, the TensorFlow framework is more widely used in industry because it is more convenient to deploy. But I personally predict that more and more people in industry will use the PyTorch framework rather than TensorFlow. Pytorch dynamic graph mechanism is superior to TensorFlow's static graph mechanism. TensorFlow must establish a session before calling graph, which brings great trouble to modification and debugging. Although Google launched TensorFlow 2.0 on October 1, 2019, it optimizes the design of TensorFlow and is closer to PyTorch in style. However, there is a big difference between tensorflow1.X and tensorflow2.X. Their API is complex, which brings extra learning cost. Obviously, people are more willing to learn and use PyTorch. The comparison of the above frameworks is shown in the table below.

Table 1 Comparison of popular deep learning frameworks

`	Core Programming Language	Interface Support	Research units
Caffe Caffe2	C++	Python, Matlab	UCB
Apache MXNet	C++, Cuda	Python, Scala,Julia, Clojure, Java, C ++, R and Perl	Amazon
TensorFlow TensorFlow2.0	Python, C++, Cuda	Python, C/C++, Java	Google
Keras	Python	Python, Matlab	Google
PyTorch	C, Lua	Python, C/C++, Java, Lua	Facebook

2.6 Prospect

After several years of development in the field of computer vision, the traditional direction of deep learning such as object detection and semantic segmentation has become saturated. The calculation results of the data set have reached the limit, and it is very difficult to improve it. This requires more detailed and extensive debugging parameters and optimized structure, but this is inseparable from the high computing power, which is very unfriendly to small research teams.

Big companies, such as Google and Facebook, have a large number of graphics cards to support large networks and massive data computing. Therefore, I personally think that it is not very appropriate for small research teams to participate in the research in this field at present, so I suggest changing to some other directions.

The author thinks that the direction of improving potential and application value at present and in the future is as follows. (1) Meticulous segmentation. That will pay more attention to the accuracy of segmentation and the degree of refinement of edge. (2) Focusing on small targets. Previous research results show that most networks can achieve good results in detecting and segmenting large targets, but the results of small targets are not satisfactory. As a result, small goals also need attention. (3) Three dimensional data processing. This year's best paper and best student paper of CVPR are research on 3D data, which will certainly promote the research in this field. (4) Neural Architecture Search (NAS). Let neural network search and optimize the network structure, instead of artificial design. The first paper on NAS was born in 2016 [103]. Since then, this field has been studied by more and more people.

3. One-dimensional data in SHM and SDD

In the field of civil engineering, one-dimensional data processing based on CNN is mainly used in the field of SHM. In the SHM system, sensors are widely arranged to collect time-varying signals in real time. The function of deep learning is to analyse the collected sensor time-varying signals, and to study and judge the structural health status, structural damage assessment, performance evaluation, structure self-diagnosis and so on. The comparison between the traditional structural health monitoring system and the structural health monitoring system based on deep learning is shown in the figure below.

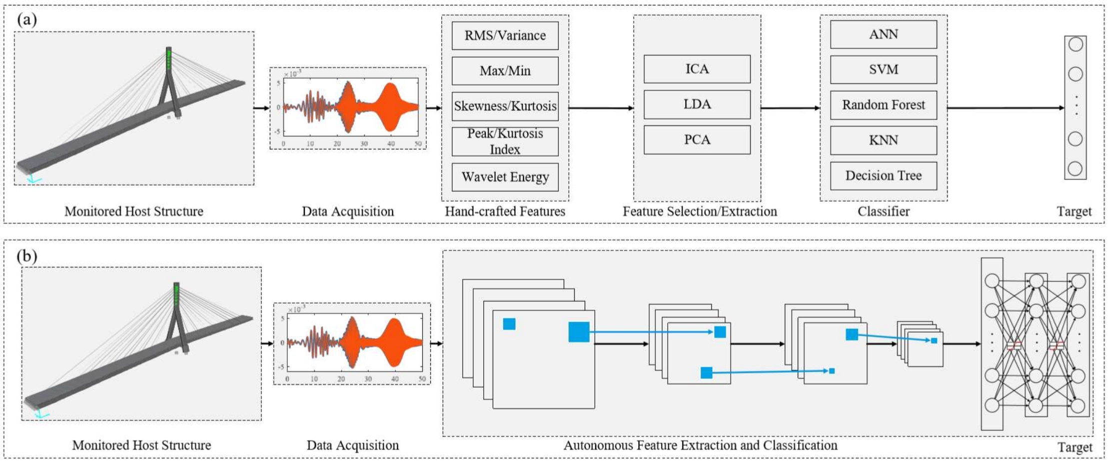


Fig. 27 Comparison: (a) Conventional data-driven SHM vs. (b) Deep learning-based SHM. [29]

Compared with the traditional system, the deep learning system avoids the complicated manual data processing, data feature selection and extraction process, and data post-processing and analysis process. It is one-step in place, and automatically realizes the data feature presentation and analysis. It is highly intelligent and greatly simplifies the manual operation.

3.1 Structural response prediction

There are two main types of research in the field of structural seismic engineering based on deep learning method, (1) prediction of structural response based on neural network and (2) location and evaluation of structural damage.

Oh *et al.* [104] proposed a prediction method for seismic response of building structures based on CNN. The input data of CNN is the seismic acceleration time history, and the output data is the predicted structural response. The following figure shows the comparison between the structural displacement predicted by neural network model and the test results in different floors. It can be seen from the figure below that the prediction results have high accuracy.

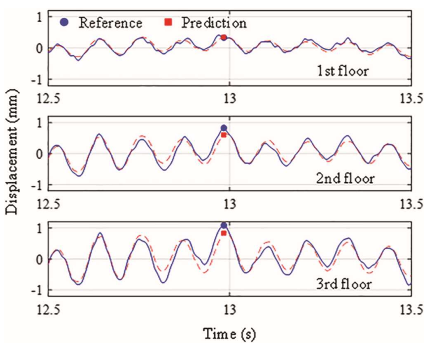


Fig. 28 Displacement prediction results

Furthermore, Oh *et al.* [105] introduced the resonance area parameter into the neural network and proposed a prediction model of building seismic response considering the correlation between ground motion and structure. The proposed resonance area parameter takes into account the dynamic characteristics of the structure, such as the natural frequency of the structure and the mass ratio of the vibration mode. Compared with the experimental results, the neural network prediction results achieve satisfactory prediction accuracy.

Zhang *et al.* [106] used the depth long short-term network (LSTM) to predict the seismic response of nonlinear structures. Different from the traditional nonlinear time history analysis methods based on numerical method, their deep learning model based on data driven can accurately predict the elastic and inelastic responses of building structures. Similar to the method of Oh *et al.* [104], the input of the network is still the seismic acceleration time history, and the output is the seismic response. Furthermore, Zhang *et al.* [107] introduced the physical information into the neural network and proposed a physically guided convolutional neural network framework, which introduced physical constraints into the neural network. An objective of neural network optimization makes the following equation tend to 0.

$$f\text{: } \ddot{\boldsymbol{y}}(t) + \boldsymbol{g}(t) = -\Gamma \ddot{\boldsymbol{y}}_g(t) \rightarrow 0 \qquad (1)$$

The PhyCNN framework is shown in the figure below. Based on the idea of PINNs [88], this framework achieves a very good prediction effect of structural response. Recently, combining the ideas of references [106] and [107], Zhang *et al.* Proposed a Multi-LSTM network based on physical information (PhyLSTM) [108]. The network uses the idea of meta learning to learn sequence features from limited data. The network uses physical laws as additional constraints, encodes them into the network architecture and embeds them into the overall loss function, which makes the model train in the feasible solution space. The model has good generalization ability and robustness.

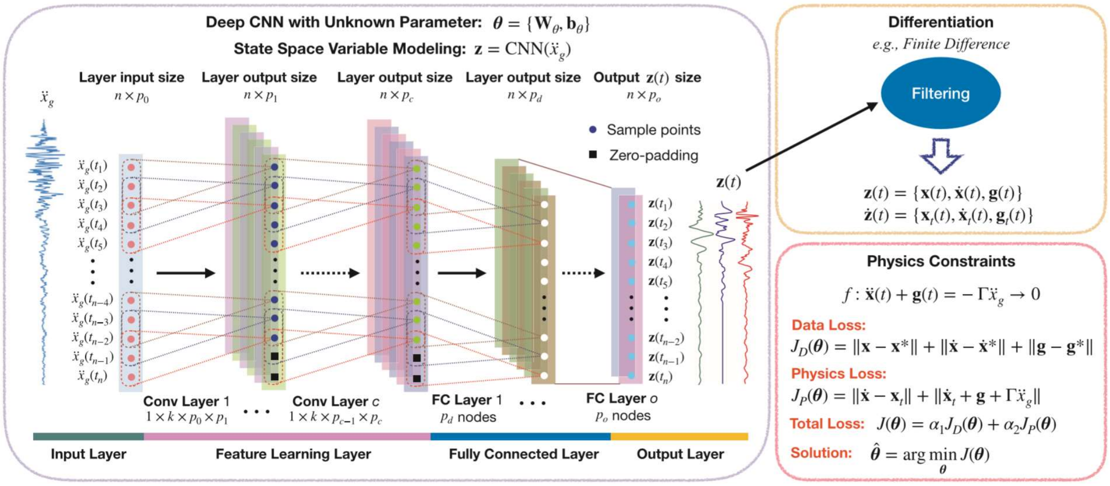


Fig. 29 Network design

It can not only predict the seismic response of the structure, but also estimate the wind-induced response of high-rise buildings based on convolutional neural network. Oh *et al.*[109] took the time history data of displacement and wind speed of the top layer of the structure as the input layer of the neural network, and took the maximum strain and minimum strain of the component as the output layer of the neural network to evaluate the safety of the components.

A response prediction method of high-rise buildings based on DenseNet was also proposed. [110] They used the method to predict the wind-induced response of Guangzhou tower. The results showed that the method could accurately reconstruct the response in time domain and frequency domain and have strong noise resistance. In addition, highly consistent modal parameters were identified from the reconstructed real response, and the applicability of the method was good. The proposed model is shown in the figure below.

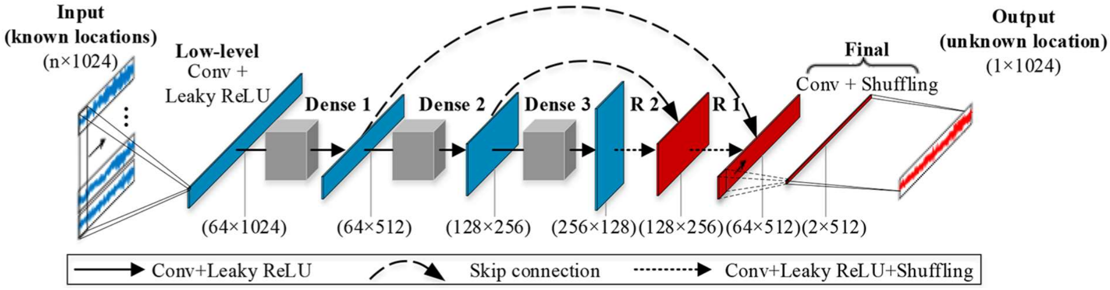


Fig. 30 The architecture of the proposed methods

3.2 SDD

Damage and performance evaluation of buildings is another application of deep learning in the field of structural earthquake resistance or wind resistance. Sajedi *et al.* [111] proposed a neural network model for structural damage location and assessment in earthquake based on FCN. The model can evaluate the performance of the structure reasonably. The structure of the model is shown in the following figure. Sajedi *et al.* [112] also proposed a robust framework for identifying the presence, possible location and severity of damage based on data-driven and cumulative strength damage features. The framework considers the uncertainty of seismic risk and the adverse consequences of misclassification in data-driven methods, and optimizes the objective function based on confusion fraction matrix. Wang *et al.* [113] proposed a deep residual network framework for health monitoring of civil engineering structures. These residual blocks are used as feature extractors and the full connection layer is added to identify damage. The results show that the model can accurately identify damage in the presence of measurement noise. Ding *et al.* [114] proposed a new method for structural damage identification based on sparse DBN. The natural frequency and mode shape of the structure are taken as the input of the network, and the output of the network is the damage location and severity of the structure. Zhang *et al.* [115] used one-dimensional CNN network to identify the location of local small changes in mass and stiffness of structures in vibration, which has high sensitivity. Azimi *et al.* [116] automatically identifies and locates structural damage from compressed structural response data (considering a variety of sensors) based on CNN.

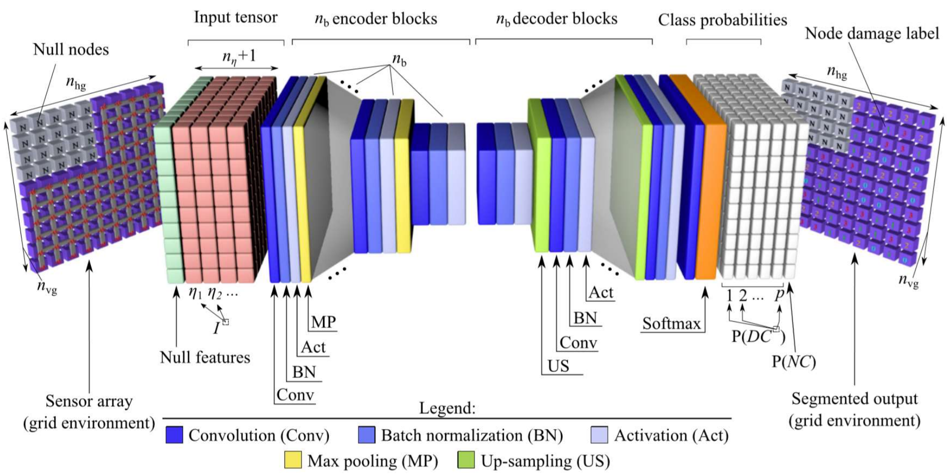


Fig. 31 The proposed deep learning architecture

3.3 Other applications

In addition to the above two popular research directions, researchers have also studied the application of deep learning in other aspects of one-dimensional data processing. Measurement noise inevitably exists in vibration data, which seriously affects the usability and quality of the measured vibration signal used for structural identification and condition monitoring. Fan *et al.* [117] proposed a vibration signal denoising method based on special residual convolution neural network (ResNet), which was suitable for harsh and extreme environments.

The signal transmission loss of wireless sensor for structural health monitoring is a common situation, which reduces the reliability of the sensor monitoring structure state. It is difficult to analyze the vibration data with high data loss rate, which will lead to serious errors. Fan *et al.* [118] proposed a data recovery method for structural health monitoring based on convolutional neural network, which still had good data recovery ability even when the data loss rate was as high as 90%. Tang *et al.* [119] proposed a continuous missing structural health monitoring data recovery method based on a kind of sparse sensing convolutional neural network.

SHM system often produces a lot of data, but the validity and availability of these data are often unknown. SHM data usually include various types of anomalies caused by sensor failure or system failure, which may interfere with structural analysis and evaluation. In the conventional data preprocessing, a variety of signal processing techniques are needed to detect anomalies respectively, which is inefficient. Tang *et al.* [120] proposed an automatic data anomaly detection method based on CNN, which could avoid tedious manual screening.

A large amount of data generated by SHM system also brings great challenges to data storage. Data compression and reconstruction as a new field of structural health monitoring of large infrastructure system emerges as the times require. Ni *et al.* [121] proposed a new data compression and reconstruction framework based on deep learning. This autoencoder structure could recover data with high accuracy at a low compression ratio (up to 10%). The proposed deep learning model of data compression and reconstruction is shown in the figure below.

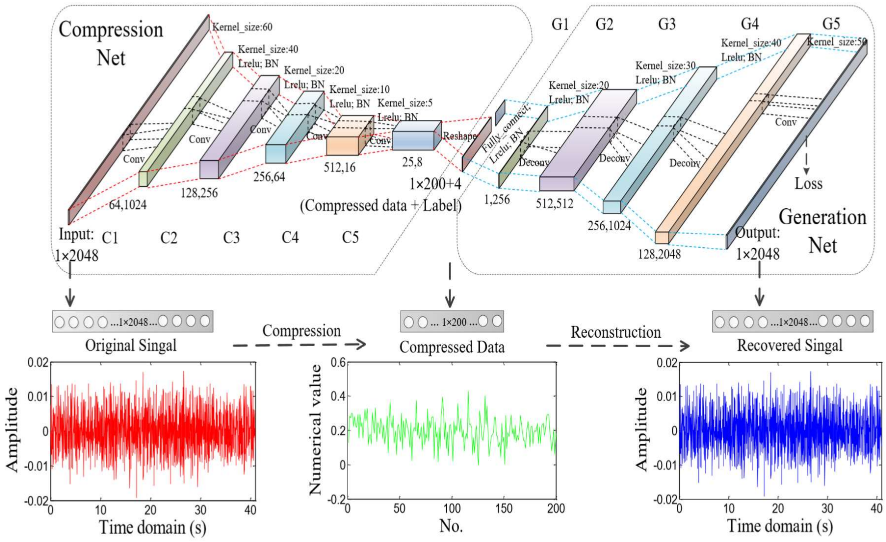


Fig. 32 The architecture of data compression and reconstruction network

4. Two-dimensional data in SHM and SDD

Similar to the development of deep learning in the field of computer vision, processing two-dimensional data in the field of civil engineering is also the earliest and most widely studied. The application in this field is mainly for the automatic detection and segmentation of structural apparent diseases such as concrete surface cracks, road cracks, concrete spalling, steel corrosion and so on. Among them, the automatic detection and segmentation of cracks is the earliest and related research is also the most.

4.1 Crack detection and segmentation

In recent years, the collapse accidents of bridges still in-service life are common. Regular health monitoring and maintenance of bridge structure is very important to delay the service life of bridge and ensure the safety of bridge. Crack is an important feature of structural safety, durability and applicability, and also an important part of bridge safety detection. Therefore, periodic crack detection plays an important role in the maintenance and operation of existing concrete structures. The traditional crack detection is mainly based on manual image acquisition, usually need to borrow assistant tripod, bridge inspection vehicle and other heavy equipment. The manual detection method has low efficiency, high cost and strong subjectivity and uncertainty. The skill level and experience of inspectors have significant influence on the accuracy of crack detection. The traditional digital image processing algorithm can better process some simple crack images, but it cannot adapt to the complex engineering environment, so its use is limited [122]-[123].

In order to improve the efficiency and objectivity of crack evaluation and make up for the defects of human based visual inspection method, people have carried out extensive research on automatic crack detection. Before the rise of deep learning methods, it was mainly machine learning methods [124]. Later, deep learning has achieved results beyond the traditional methods in many computer tasks, and its application in the field of civil engineering crack detection has also attracted people's attention.

In 2017, Cha *et al.* [125] published the first paper on crack detection using deep learning in the top journal Computer Aided Civil and infrastructure engineering in the field of civil engineering, which was also the first application of deep learning method in the field of civil engineering. Cha *et al.* Designed a convolutional neural network framework to realize the block target detection of cracks. As of July 10, 2020, the number of citations of this paper has reached **567** (from Research gate data). In the field of civil engineering, there is no doubt that this paper has great influence and inspiration. In the same year, Lin *et al.* [126] designed a convolutional neural network to learn features and identify damage locations. It has good positioning accuracy on both noisy and noisy data sets. After that, more and more researchers began to study the cross combination of deep learning and civil engineering. Yang *et al.* [127] realized the semantic segmentation of crack image at pixel level based on full convolution network FCN, which provided the basis for the quantification of crack length and width. Ni *et al.* [52] drew lessons from the design ideas of GoogleNet and the idea of feature fusion, and put forward a new pixel level structure damage detection and segmentation method CDN based on image. This method can realize fast, high precision and automatic crack identification and segmentation. The following figure shows the integrated network framework of crack identification and segmentation.

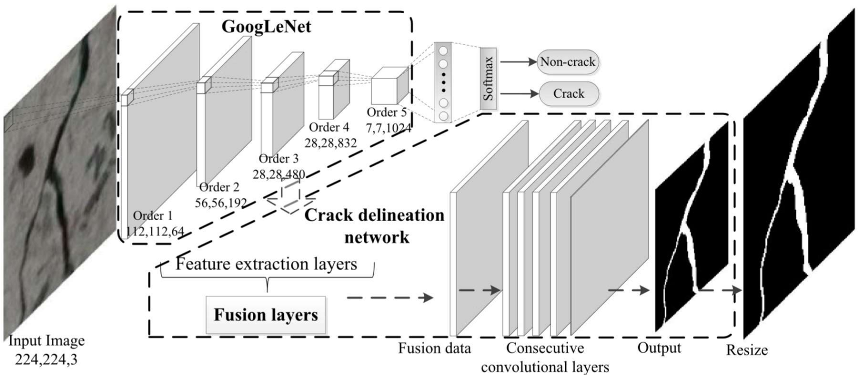


Fig. 33 The architecture of CDN

Subsequently, a double scale convolution neural network is proposed for quantitative measurement of crack width. Based on Zernike moment operator, the measurement accuracy can be improved to sub-pixel level [53]. Later, Liang [128] took the multi-scale convolution neural network further and proposed a three-level post disaster detection method for reinforced concrete bridges. A convolutional neural network based on image classification, target detection and semantic segmentation is proposed for system level fault classification, component level bridge pier detection and local damage level damage location.

In recent two years, many researchers have innovated on the convolutional neural network for crack detection and segmentation. Instead of blindly selecting some traditional convolutional neural networks, many novel neural networks and algorithms have been used in the field of crack detection and segmentation. Zhang *et al.* [129] proposed a context aware fusion algorithm considering local crossing state and cross space constraints and combined it with deep convolution neural network to realize automatic semantic segmentation of images of any size. The average processing time of a single image is only 0.7 seconds. Based on the dense connected deep neural network (DenseNet), Mei *et al.* [130] proposed an automatic crack segmentation method and used it in the direct image shooting of smart phones [131]. The system method has good generalization ability. The figure below shows the detail of the density block adopted. Choi and cha [132] proposed a real-time crack detection method SDDNet, which consisted of standard convolutions, densely connected separable convolution modules, a modified Atrous spatial pyramid pooling module, and a decoder module. The network can process 1052 × 512 pixel images at 36 frames per second, which is 46 times faster than the latest work. Kang *et al.* [133] proposed an improved scheme of Faster R-CNN which was combined with the modified tubularity flow field algorithm (TuFF). At last, automatic crack detection, segmentation and quantization in pixel level complex background were realized, and the average accuracy could reach 95%.

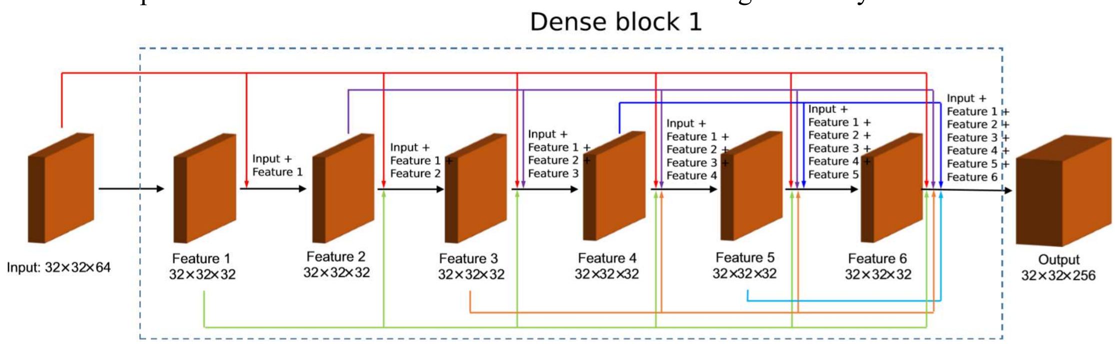


Fig. 34 Details of dense block 1.

Not only the surface of building structure will have cracks, but also pavement cracks and diseases cannot be ignored. Many researchers have done research in the field of pavement crack automatic detection. Tong et al. [134] used convolutional neural network to detect pavement diseases earlier. Maeda *et al.* [135] used convolutional neural network to automatically detect and classify cracks in pavement images directly taken by smart phones, which broadened the application range. A road disease data set is also released, which can promote the detection and segmentation of road diseases. Zhang *et al.* [136] used recurrent neural network to segment cracks in asphalt pavement at pixel level. Subsequently, Tong *et al.* [137] proposed an automatic pavement crack segmentation method based on FCN and Gaussian conditional random field, which realizes fine segmentation of pavement cracks and has good generalization ability. The proposed method is shown in the figure below. Mei *et al.* [138] proposed a cost-effective solution for pavement crack detection based on vehicle mounted camera and deep learning and introduced the idea of generative adversarial network (GAN), which can realize fast and real-time segmentation of pavement cracks. Based on GAN, Maeda *et al.* [139] generated a large number of pavement disease photos as training data, which improved the detection accuracy of pavement disease.

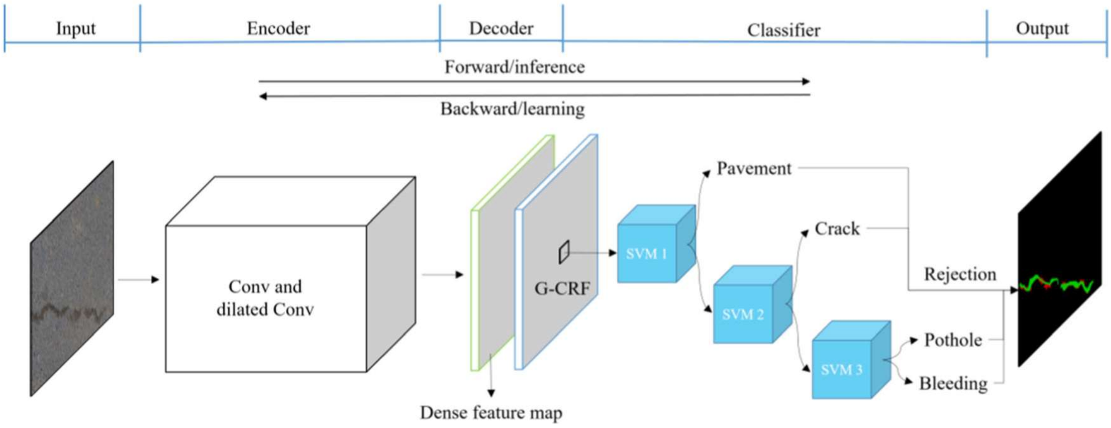


Fig. 35 Architecture of the network

4.2 other diseases of concrete structures

Cracks are only one kind of apparent diseases of concrete structures, and common diseases include concrete spalling, holes and exposed reinforcement. Li *et al.* [140] proposed a FCN based multi damage detection and disease segmentation method for concrete structures, and collected 2750 images containing various diseases for training and testing. The results show that the segmentation accuracy of the proposed method can reach 91.59%. Xu *et al.* [141] proposed an improved Faster R-CNN network, which can identify and locate various types of post-earthquake damage of damaged reinforced concrete columns from images, including concrete cracking, concrete spalling, reinforcement exposure and reinforcement buckling. The proposed method can automatically identify and locate multiple types of earthquake damage, and the average accuracy can exceed 80%. The identification results of some earthquake damages are shown in the figure below. Zhang *et al.* [142] put forward an automatic detection method for concrete bridge damage based on yolov3 network, which can detect cracks, pop out, cracks in real time. There are four kinds of diseases, such as spalling and steel bar exposure.

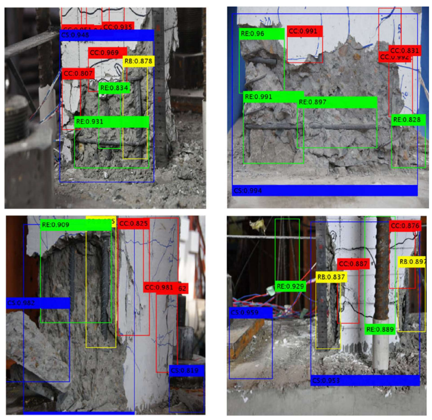


Fig. 36 Identification results

4.3 Damage detection of steel structures

Deep learning is not only applied in concrete structure disease detection, but also introduced into steel structure detection by researchers.

Corrosion of steel structure is one of the main diseases of steel structure. Ali *et al.* [143] introduced the deep learning method into the corrosion detection of steel structures. An automatic detection method based on deep learning and uncooled micro bolometer is proposed. The neural network does not detect the steel structure image directly, but detects the infrared image, which can obtain higher detection accuracy. The detection framework proposed by Ali *et al.* is shown in the figure below.

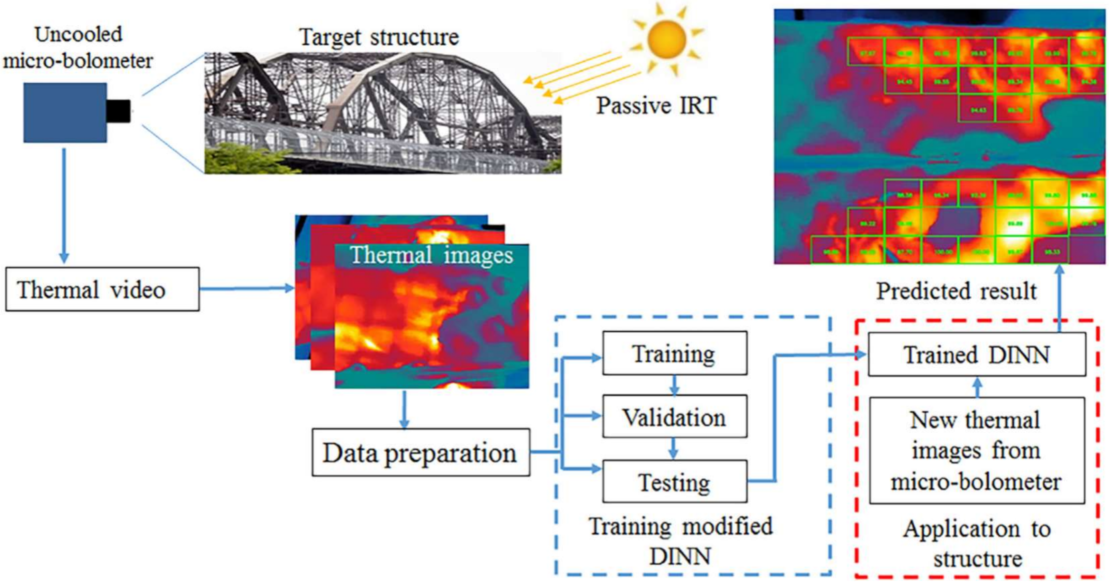
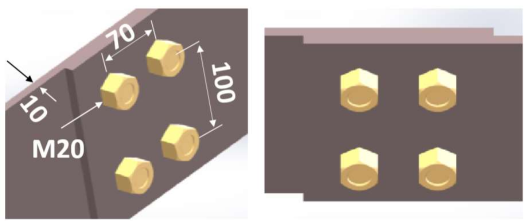


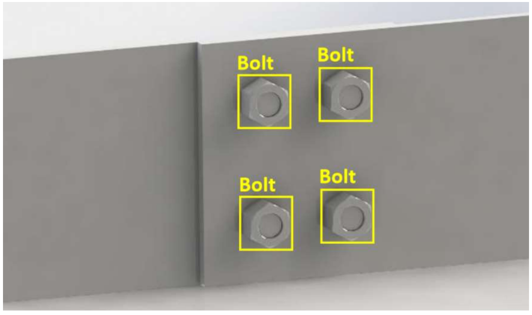
Fig. 37 Schematic view of the proposed subsurface damage detection method

Some researchers have studied the bolt detection which is widely used in steel structure. As an important part of steel structure, bolt damage will affect the safety of the structure, and even lead to serious accidents, so the research in this field is of great significance. Zhao *et al.* [144] combined deep learning with machine vision and proposed an automatic detection technology of bolt loosening angle, with the overall recognition accuracy of 0.914. The model was transplanted into smart phones to realize fast and simple bolt loosening monitoring.

Pham *et al.* [145] do not directly based on the real bolt image, but combine deep learning with computer graphics, and use the synthesized bolt image to train the deep learning model for bolt looseness detection. The feasibility of the frame is verified by a laboratory bolt connection model and real bridge test. This method can reduce the time and cost of collecting high-quality training data by using synthetic data for neural network training and has the prospect of popularization and application. Bolt detection based on computer 3D model is shown in the following figure.



(a)



(b)

Fig. 38 3D detection model. (a) Parameterized graphic models under different perspectives; (b) A typical synthetic image with bounding boxes.

4.4 Damage detection of ancient buildings

The detection and detection of historical glazed tile damage plays an important role in the maintenance and protection of historical buildings. However, the current visual inspection methods used to identify and evaluate the surface damage of historic buildings are time-consuming and laborious. Wang *et al.* [146] first introduced the deep learning method into the apparent damage detection of ancient buildings. A two-stage detection method is proposed, as shown in the figure below. Firstly, the Faster R-CNN network is used to detect the defects of glazed tile photos, and then the pixel level segmentation of the defects based on Mask R-CNN is carried out to quantitatively analyze the damage characteristics.

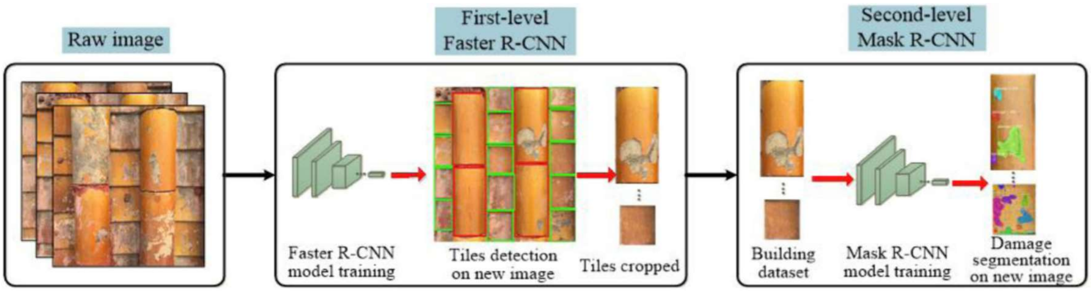


Fig. 39 Flowchart for the two-level object detection strategy

4.5 Intelligent construction

Intelligent construction and operation and maintenance in the field of civil engineering is one of the important directions for the future development of civil engineering, in which intelligent construction is the key link.

Many researchers also apply deep learning technology to the construction to improve the intelligence and automation of the construction process.

Arabi *et al.* [147] put forward an improved MobileNet model, which can effectively detect engineering vehicles, and verify the practicability of the target detection solution for construction scene based on deep learning, which can be used for intelligent monitoring, productivity evaluation and management decision-making.

Shen *et al.* [148] proposed a safety helmet wearing detection method based on convolutional neural network face detection and boundary box regression. Based on DenseNet deep transfer learning and mutual distillation method, this method can effectively detect small multi-scale helmets, and the average detection accuracy reaches 94.47%. It is an important part of safety management to detect the wearing condition of workers' safety helmets, which can effectively reduce the death rate of construction accidents. This study has a strong practical significance and potential for popularization and application. The basic framework of the model is shown in the figure below.

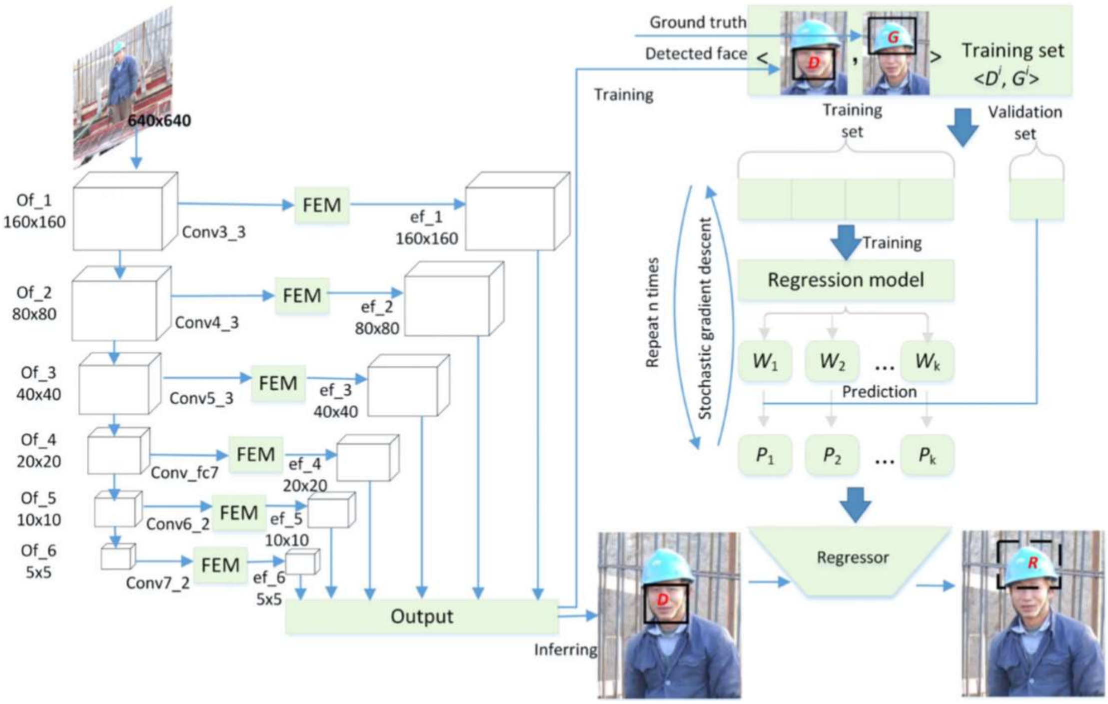


Fig. 40 Basic framework of the model

4.6 Other applications

Displacement monitoring is always an important branch of structural health monitoring. Multi point displacement monitoring can not only reduce the monitoring cost, but also improve the monitoring efficiency. Zhang *et al.* [149] proposed a multi-point displacement monitoring method based on FCN and smart phone. The test results show that the monitoring errors are less than 1% at 2.5m and 5m, and 1.696% and 1.997% at 7.5m and 10m, respectively. The method can meet the needs of practical engineering, and the cost is greatly reduced by using smart phones.

5. Three-dimensional data in SHM and SDD

The development of 3D scanning equipment and related algorithms promotes the development of automatic driving and slam. In the field of civil engineering, the application research of 3D data has also attracted many scholars' attention. The author thinks that 3D point cloud data has a broad application prospect in the field of civil engineering. Through three-dimensional scanning, people can build the actual three-dimensional model of building structure, which can be combined with Building Information Model (BIM) and finite element technology, and transformed into BIM model and finite element model, so as to study structural deformation, evaluate health status and management of operation and maintenance. This is the classic idea of digital twin, which has broad application prospects.

Furthermore, the research scale can be expanded from single building to complex buildings or the whole city. Lu *et al.* [150] of Tsinghua University proposed a multi disaster simulation framework based on city information model (CIM), which considered three types of disasters, namely earthquake, fire and wind. The framework consists of three modules: (1) data transformation, (2) physics-based hazard analysis, and (3) high-fidelity visualization. The framework also has three significant advantages. (1) The database with multi-scale models is capable of meeting the various demands of stakeholders. (2) Hazard analyses are all based on physics-based models, leading to rational and scientific simulations. (3) High-fidelity visualization can help non-professional users better understand the disaster. The multi-hazard simulation framework for CIM is shown in the figure below.

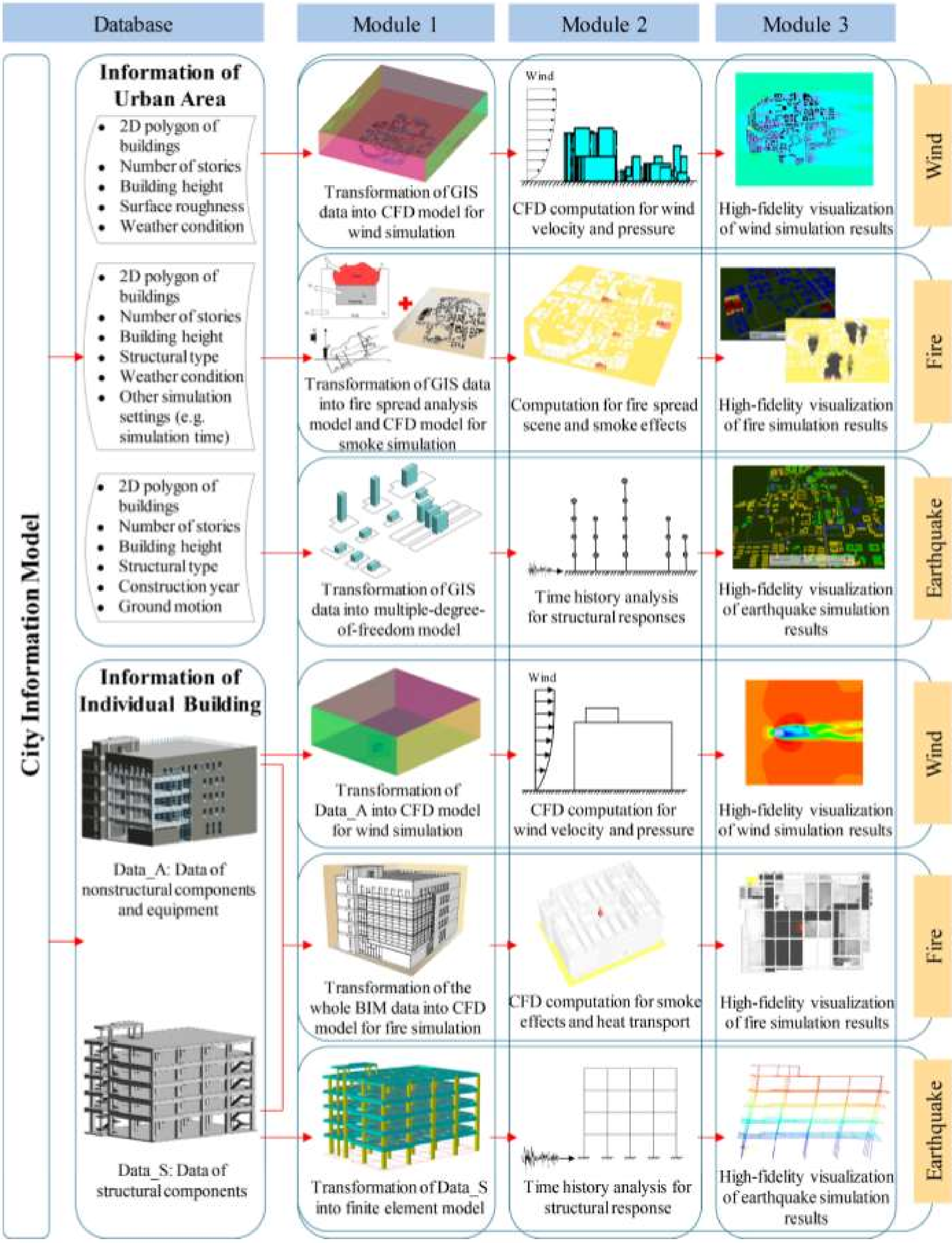


Fig. 41 The proposed multi-hazard simulation framework for both individual buildings and urban areas.

It can be seen from the above that the key step is to transform the solid model into the digital model, and the current research mainly focuses on this direction. Lu *et al.* [151] Based on cluster analysis, proposed a method to identify pier, pier cap, beam and bridge deck from point cloud data of reinforced concrete bridge. Liu *et al.* [152], not based on the point cloud data, but based on the image data, proposed a method of pier 3D reconstruction and pier crack detection based on multi view images. The effect of crack identification is shown in Figure 42, and the reconstructed 3D model of pier is shown in Figure 43.

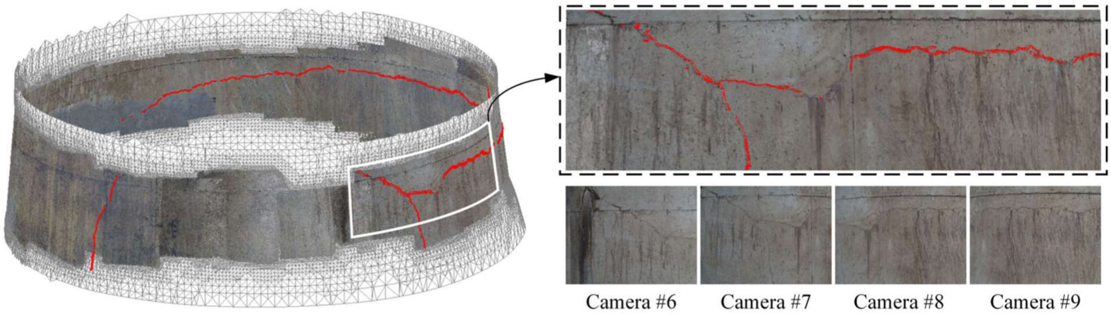


Fig. 42 Three-dimensional reconstruction and cracks detetion

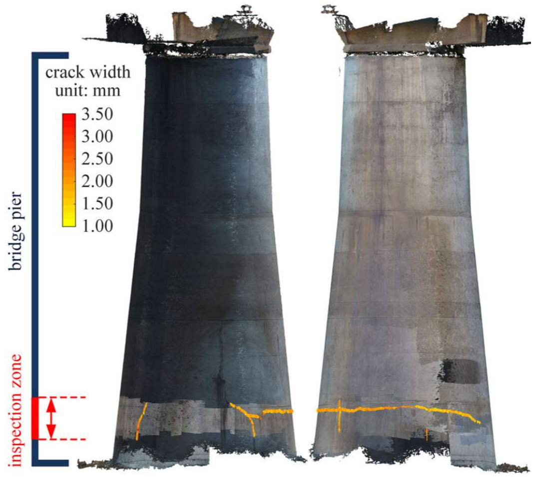


Fig. 43 Three-dimensional reconstruction

The work of the above two articles are based on traditional machine learning methods or computer vision methods, which can achieve good results in the reconstruction of simple objects and small-scale buildings. However, the actual buildings, bridges and so on are often very complex, there are many local characteristic areas, the traditional methods mentioned above are difficult to have a better effect. As described in Section 2, in the field of computer science, 3D point cloud processing based on deep learning has been widely concerned, and a lot of research results have been achieved, and many classic models have been proposed. For example, the original PointNet [97], and PointNet++ [98], which pays more attention to local features, and so on. In this year's CVPR 2020, many researchers also proposed a very novel network, such as PV-RCNN, a high-performance 3D target detection framework based on 3D CNN network [153]. Firstly, voxels are coded into 3D scenes, and then ROI features are extracted. The framework is shown in the figure below.

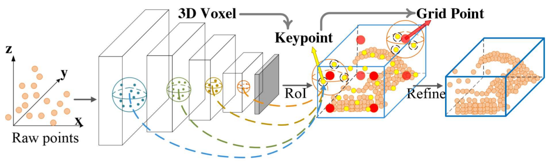


Fig. 44 PV-RCNN framework

Xu *et al.* [154] proposed a fast and extensible framework Grid-GCN based on 3D graph convolution network. Grid-GCN adopts a new data structure strategy, and Coverage-Aware Grid Query (CAGQ). It also uses Grid Context Aggregation (GCA). CAGQ can improve the spatial coverage and reduce the theoretical time complexity. Grid-GCN achieves state-of-the-art performance on major point cloud classification and segmentation benchmarks and runs much faster than previous studies. Grid-GCNuses 81920 points as input on ScanNet, and its reasoning speed reaches an amazing 50FPS! The network idea is shown in the figure below.

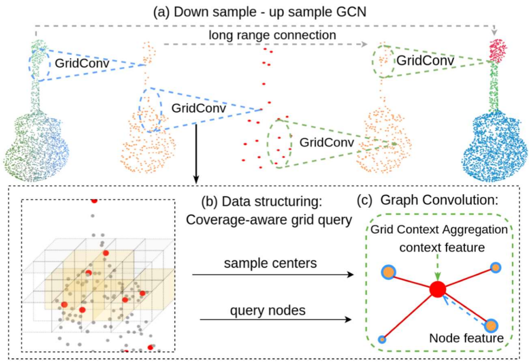


Fig. 45 Overview of the Grid-GCN model

However, the application of deep learning method in 3D point cloud target detection and segmentation of building structure is less, only two related works are found, and both of them are published recently. This indicates that this field is still very novel and needs further development.

Kim *et al.* [155] proposed an automatic bridge component recognition method based on deep learning, which can deal with point clouds in the background area, and greatly reduce the time consumption of point cloud pre-processing. The recognition results of this method are shown in the figure below.

It can be seen that the point cloud of simple components with large shape difference, such as bridge deck and pier, is segmented with high precision.

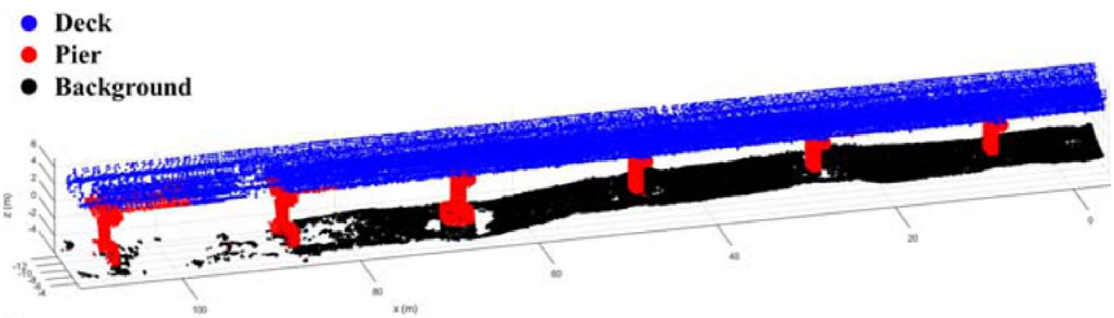


Fig. 46 Segmentation results

The last work is to carry out the three-dimensional reconstruction of concrete beam bridge.

Hu et al. [156] recently proposed a 3D reconstruction method for cable-stayed bridges based on deep learning and structural perceptual learning, and the results are robust to noise and incomplete scanning. The accuracy of the results obtained by this method is similar to that of the manual reconstruction method, but it can improve the reconstruction efficiency. The limitation of this method is that it only has a good reconstruction effect but does not automatically segment the components. This is also the next research direction.

The method flow is shown in the figure below.

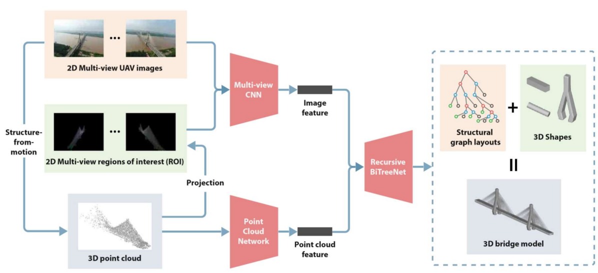


Fig. 47 Framework of the proposed solution

6. Intelligent detection equipment

In recent years, many researchers have developed a variety of intelligent detection equipment to replace the traditional artificial detection.

Xue *et al.* [157] and Huang *et al.* [158] developed a Mobile Tunnel Inspection (MTI) for automatic image acquisition, and then realized the automatic detection of tunnel lining defects based on FCN segmentation algorithm. This method can be used to identify defects quickly and accurately in the structural health monitoring and maintenance of subway shield tunnel. The following figure shows the tunnel detection image acquisition equipment developed by them.

Menendez *et al.* [159] also developed a shield tunnel disease detection robot, which is composed of mobile vehicles, cranes and high-precision manipulator.

Compared with Xue and Huang's devices, the robot can take pictures close to the surface of the structure and obtain higher quality images. But the problem of these intelligent devices is that they only have the function of image acquisition and have no function of image processing. There is a lack of intelligence.

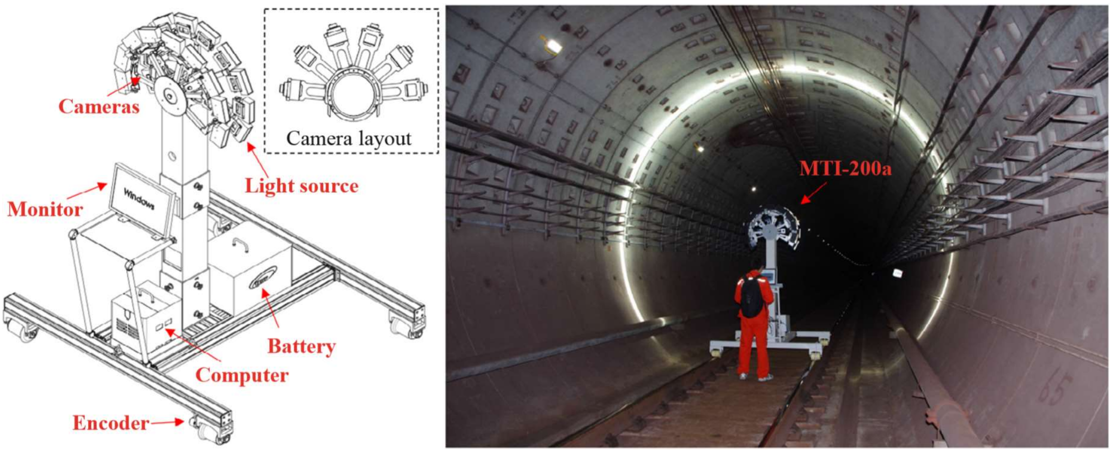


Fig. 48 Metro Tunnel Inspection(MTI)

Due to the large size of bridge structure or building, there are many places difficult to reach by human.

Recently, many researchers use UAV to detect infrastructure diseases. UAV is easy to operate, light and portable, and has powerful functions, so it is expected to be widely used in civil engineering.

Metni *et al.* [160] earlier began to use UAVs with cameras to detect bridge cracks. In 2019, Shang Jiang and Jian Zhang [54] proposed a novel UAV system by combining UAV with wall climbing robot and realized real-time detection of structural surface cracks based on smart phone and deep learning model. The following figure shows three modes of wall climbing UAV, namely normal flight mode, wall close mode and roof close mode. Compared with the traditional UAV, the UAV can find more subtle diseases through close observation. Tian *et al.* [55] realized non-contact cable force real-time measurement based on video information captured by UAV. In addition, Wen Yi and Monty Sutrisna [161] used UAVs to monitor the construction site and established an optimal UAV scheduling model. This model could ensure that the UAV spends the most time in the key sites, while the total flight time was the shortest, and did not run out of battery power.

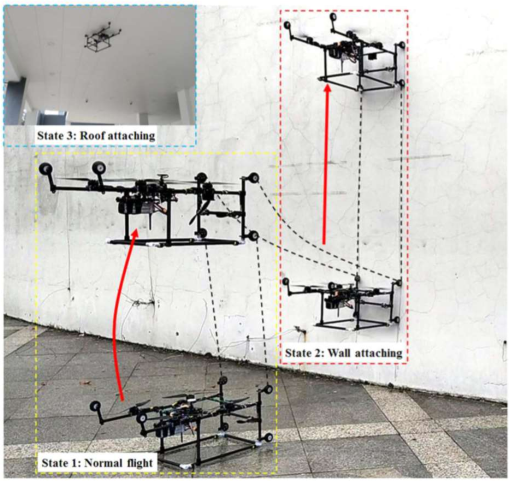


Fig. 49 Three states of wall-climbing UAS in inspection

Additionally, researchers have developed a variety of special robots.

La *et al.* [162] developed a visual camera embedded vehicle type magnetic climbing robot for steel bridge detection. Gibb *et al.* [163] proposed a concrete bridge detection robot composed of ground penetrating radar, two resistivity sensors and a camera system. Li *et al.* [164] proposed a climbing robot with a visual camera for cable inspection. Jang *et al.* [165] developed a ring-shaped wall climbing robot system for high-rise piers, which is composed of a visual camera, a wall climbing robot and a control computer. It can achieve automatic climbing, obtain high-quality visual images and automatic segmentation and quantification of cracks, and the recognition accuracy can reach 90.92%.

The following figure is the schematic diagram of the climbing robot system.

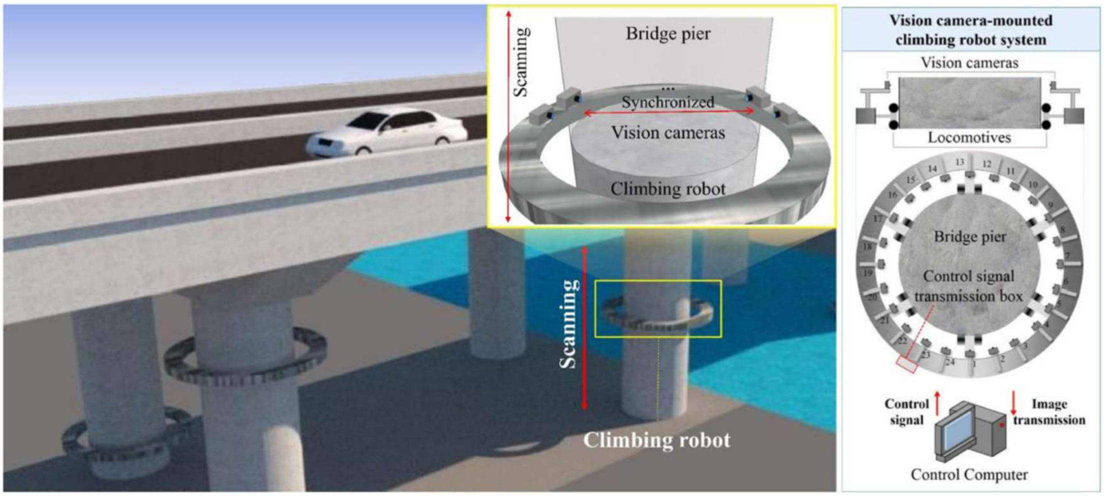


Fig. 50 Schematics of the vision camera-mounted climbing robot system

Automatic and intelligent detection equipment will be more intelligent and intelligent in the future and will replace manual detection. Therefore, the detection time and cost can be saved. This is also one of the directions of intelligent construction and operation and maintenance. I hope it can be realized as soon as possible

7. Research gap

I will be similar to the previous logic, according to one-dimensional data, two-dimensional data, three-dimensional data and intelligent devices to list the main points. The following problems are also some of the problems that I have found of great research value since I have been exposed to artificial intelligence for more than a year. I will also try to solve these problems in my future graduate career and contribute my modest strength to this field.

7.1 One-dimensional data

At present, I have little contact with one-dimensional data. Personal feelings can be explored in combination with PINNs. Because there are a lot of partial differential equations and ordinary differential equations to solve in the field of civil engineering. Such as statics and vibration. These problems can be solved by using PINNs, which can avoid the complex pre-processing finite element modeling process.

7.2 Two-dimensional data

In the field of two-dimensional data, there has been a lot of research, but I personally think that there are still some key scientific problems that have not been well solved. The following directions are found in the long-term reading of the literature, and the current research is not very mature.

(1) Fine and fuzzy crack detection

The future intelligent algorithm will be combined with intelligent detection equipment. Because the detection equipment is moving, and the focal length and observation distance may not be optimal, the shooting results must have the problems of fine cracks and fuzzy. It is necessary to develop the detection algorithm of this kind of crack. This also involves the basic task of small target segmentation in computer vision.

(2) Few-shot and zero-shot learning

At present, a large number of images (usually thousands) need to be marked manually, which is time-consuming and laborious. And in many cases, it is difficult to obtain a large number of high-quality data. Therefore, it would be very meaningful to achieve high quality disease detection and better generalization ability in the case of only dozens of samples or no samples. This also involves the basic task of few-shot and zero-shot in computer vision, and also involves the field of unsupervised learning. At present, the research of few-shot is mainly focused on the field of image classification. There are not many studies on target detection and semantic segmentation because of the difficulty. This is also a promising direction.

(3) Cable force measurement based on deep learning

At present, the cable force measurement based on industrial camera or UAV has been studied by many researchers. However, the extraction of cables is still based on traditional edge detection methods. For the actual bridge, the background of the cable is sometimes very complex, so the traditional edge detection method is no longer applicable, and the segmentation accuracy is difficult to guarantee, which will lead to the difficulty in practical engineering application, more stay in the laboratory. Edge detection based on deep learning has been paid more attention in recent two years. Compared with traditional methods, this method has higher segmentation accuracy, wider application range, and has the potential of practical engineering application. However, it has not been seen that this method is combined with cable force measurement.

I personally think it is a very meaningful direction.

(4) Underwater damage detection

The current research is mainly aimed at the disease detection of water structure. But for bridges and other structures, the safety of underwater piers, caps and other structures is also worthy of attention. The traditional detection method is to send divers to explore, or to explore based on sonar equipment. The first is that the efficiency is low, and the second is that the cost of launching divers is high, and the safety is difficult to guarantee. At present, there is an urgent need for robots and related intelligent detection algorithms that can be suitable for underwater disease detection. Because the water will refract the light and there are many impurities in the water, there are many differences between the photos taken in the water and those in the air, and there will be atomization and discoloration. Therefore, the development of artificial intelligence algorithm is very important.

7.3 Three-dimensional data

Last year, I proposed that 3D-CNN or GNN can be used to detect or segment structural point cloud data. There were no related papers published at that time. Then, from May to June this year, two papers on point cloud data processing using deep learning method were published, namely references [155] and [156]. It's a pity that I didn't put the idea into practice at that time.

However, one of them is to segment the components of small-scale girder bridges, and the other is to reconstruct large-scale cable-stayed bridges. At present, there is no automatic segmentation and reconstruction method based on deep learning technology for 3D point cloud of large-scale and complex shape bridges or buildings. Moreover, the calculation efficiency of the methods used in the two papers is low, and it needs a fairly high configuration computer, which is difficult to be effectively popularized and applied. Therefore, it is also a very good direction to deal with the point cloud data quickly.

In addition, there are few papers on BIM model and finite element model after obtaining 3D model. There is no paper to think from the perspective of digital twins. This is also a very good direction.

7.4 Research and development of intelligent detection equipment

As mentioned above, a considerable number of intelligent detection devices have come out. However, there is no suitable robot for bridge bottom detection. UAV flying in this area will cause GPS signal loss, unable to control. At present, the mainstream method is still based on manual rowing. However, in the case of insufficient clearance under the bridge as shown in the figure below, it is difficult to enter by manual rowing. Therefore, there is an urgent need for a robot to effectively detect the disease under the bridge.

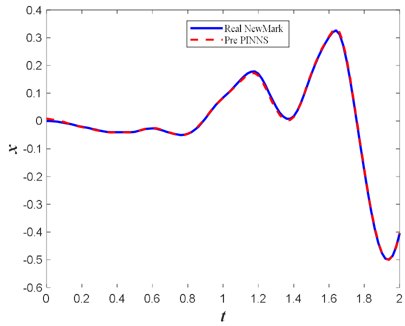
Fig. 51 Insufficient clearance under the bridge

8. Research plan and method

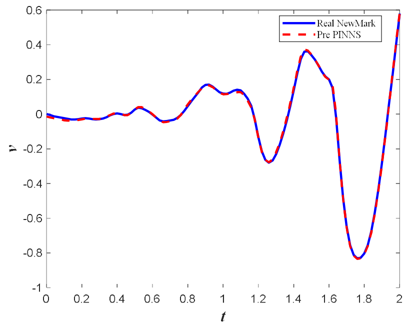
In response to the questions raised in Section 7, I have studied some of them, and some have only a preliminary idea, which has not been put into practice. I will briefly introduce my research plan and methods.

8.1 One-dimensional data

Because some scholars have already studied linear elasticity, I studied the forward and inverse problems of vibration equation based on PINNs some time ago. The following Figure (a) is a comparison of displacement solution of single degree of freedom system under EI Centro wave excitation and Newmark -β method. You can see that the two results are very close. The following Figure (b) shows the speed comparison. In addition, the displacement of MDOF system is solved. I also discussed the solution of the inverse problem. We successfully used PINNs to solve the mass, stiffness and damping of the unknown system without any finite element model or Bayesian method. Due to space constraints, I will not elaborate here.



(a)



(b)

Fig. 52 Calculation results. (a) Displacement comparison; (b) Velocity comparison.

8.2 Two-dimensional data

(1) Fine and fuzzy crack detection

The plan is divided into two phases. The first stage is to extract fracture features based on DenseNet. DenseNet can extract more detailed features because of its dense connection. In the second stage, based on the GAN and knowledge distillation [166], [167], the features extracted in the first stage are optimized to continuously improve the segmentation accuracy of fine and fuzzy cracks. The figure below shows the comparison of the F-measure values in the first stage and the second stage. It can be seen that the generation of confrontation network and knowledge distillation can significantly improve the segmentation effect. It is also compared with the traditional FCN-VGG-19. Compared with FCN-VGG-19, the proposed scheme has twice speed and 4% higher accuracy.

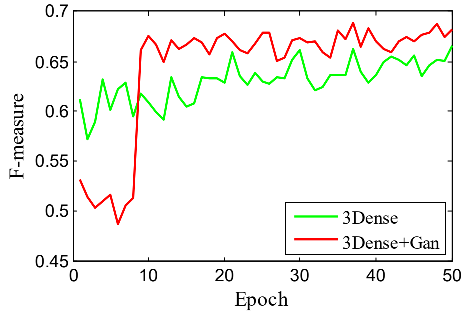


Fig. 53 Comparison of different networks

(2) Few-shot and zero-shot learning

From May to June this year, there were also two articles involving few-shot learning. Guo *et al.* [168] proposed an automatic classification technology for surface diseases. This method was based on the idea of meta learning, and the weight of training data was redistributed. The classification accuracy was improved from 71.43% of the basic CNN model to 82.86% of the CNN model based on meta learning. Xu *et al.* [169] proposed a small sample meta learning paradigm based on nested attributes, which could be used for structural damage classification. Compared with the conventional supervised learning model, this method had higher accuracy and better robustness.

Both methods are based on meta learning (a method to deal with small sample problem). But recently, some papers in the field of computer science have found that the classification result is better than the meta learning method full of tricks by combining EMD, Cosine Distance and Euclidean Distance, and it is also better than traditional machine learning classification methods such as DT, SVM, RF and clustering analysis. We can get the result of SOTA. As the so-called road to simplicity, the stack of tricks is often not a very good solution. Compared with the meta learning method, it should be a better idea to deal with the small sample problem from the most basic problems.

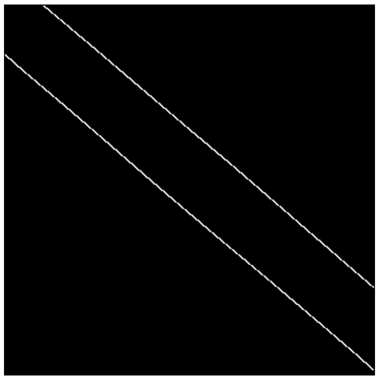
In addition, when the number of samples is small, objective detection and semantic segmentation are more challenging and promising methods. It is more meaningful than simple image classification. This is worthy of further study.

(3) Cable force measurement based on deep learning

Firstly, the method of semantic segmentation based on edge perception is used to segment the cables accurately, and then the deformation of cables is extracted to calculate the frequency of cables. Then based on the traditional frequency method or "Five Point Method", the cable force can be obtained. Of course, it is a challenge to get the displacement information from the segmented cables. At present, there are three ideas. (1) Method Based on sub-pixel Edge. (2) The upper and lower edges and midlines are extracted to improve the accuracy. (3) The output of the neural network is approximately regarded as the probability that a certain pixel is a cable.

The core innovation of the whole cable force extraction method is to propose an accurate cable segmentation method suitable for complex background. The following Figure (a) shows the segmentation of cables using neural network, and the following Figure (b) shows the segmentation scheme of traditional Canny operator. Obviously, the edge of the former is smoother and closer to the actual edge. The edge of the latter is full of sawtooth, so the precision is low

(a)



(b)

Fig. 54 Calculation results. (a) Deep learning; (b) Canny operator..

(4) Underwater damage detection

At present, the short-term plan is to develop an artificial intelligence algorithm suitable for detecting underwater images, and the long-term plan is to develop underwater robots to realize real-time detection of diseases.

As analyzed in Section 7, there are atomization and color changes in underwater images compared to those in the air. There are two ways to turn underwater pictures into images in the air and train and test them together with pictures in the air. Another idea is to transform the images in the air into images with the characteristics of underwater images, expand the data set, and train and test them together with the underwater pictures. Because underwater pictures tend to be small. According to the first idea, Hashisho *et al.* [170]

proposed an underwater image color recovery network based on u-net. This is a method worthy of reference.

My plan is to learn from the idea of reference [170] and combine with the generation of countermeasure network. First, the underwater image will be transformed into the image with air image characteristics, and then the disease detection and segmentation of the image can be carried out to solve this problem. This needs further study.

8.3 Three-dimensional data

As analyzed in Section 7, there is a lack of efficient automatic segmentation networks suitable for large-scale and complex structures. According to the ideas of references [153] and [154], I plan to improve the method and propose an efficient segmentation network suitable for multi-scale and complex infrastructure. The network is currently planned to be based on 3D-CNN. Because 3D scanning data is very large, and fine scanning is time-consuming, it is impossible to have more groups of data in the data set. It is planned to segment the bridges and houses and expand the data set.

Because of the large-scale structures with three-dimensional spatial scales of 100 meters and tens of meters, there are many point clouds, reaching 10 ^ 8 or even 10 ^ 9.Processing this kind of data brings great challenge to CPU, GPU and memory. For ordinary computers, it takes a lot of time. Therefore, fast and efficient network design is the focus of this problem.

In addition, the long-term goal is to think from the perspective of digital twins. After model segmentation, BIM model and finite element model of structure are further discussed. At present, there has no clear idea to carry on it .

8.4 Research and development of intelligent detection equipment

After the preliminary investigation, I think the unmanned ship can perfectly adapt to the detection under the bridge. Due to the low height of the unmanned ship, it can enter the bottom of the bridge when the clearance under the bridge is insufficient.

It is planned to install wireless control system, course stabilization system, GPS positioning and navigation system, Hikvision night vision camera, 7-fold zoom brushless pan tilt camera, Microsoft Kinect structured light depth camera, lidar and other equipment, as well as an airborne artificial intelligence algorithm computer. For regions with strong GPS signal, GPS is used for navigation, otherwise, lidar is used for autonomous navigation. At the same time, it is also planned to develop the autonomous return function to ensure the safety of the machine.

The main function of unmanned ship is to automatically detect the cracks, exposed reinforcement and other apparent diseases at the bottom of the bridge. This is of practical significance for the old bridges whose drawings are lost, and the changes of bridge shape can be mastered. The figure below shows the three-dimensional schematic diagram of the designed unmanned ship.

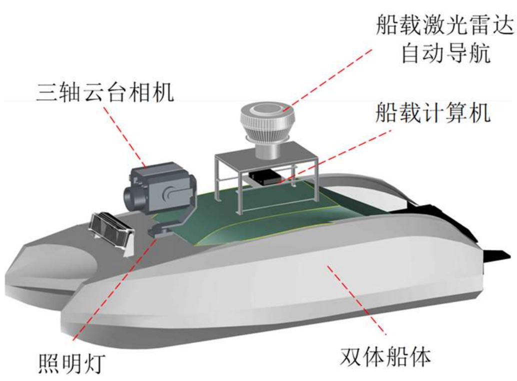


Fig. 55 Three-dimensional schematic diagram of the designed unmanned ship

9. Conclusion

The advantages of deep learning technology in the field of civil engineering health monitoring and disease detection are obvious. In recent years, the research shows exponential growth. This paper reviews the application and significance of deep learning technology in health monitoring and disease detection. This paper summarizes the current research from the perspectives of one-dimensional data, two-dimensional data, three-dimensional data and intelligent detection equipment.

(1) The application research in one-dimensional data mainly includes structural response prediction under earthquake or wind excitation, loss location and performance evaluation of buildings, as well as denoising, data recovery, data anomaly detection and data compression of structural health monitoring signals.

(2) The application of the two-dimensional data mainly includes: automatic detection and segmentation of cracks in concrete structure or pavement, automatic inspection of concrete structure spalling, exposed reinforcement and other diseases, steel structure corrosion detection and bolt loosening detection, ancient building damage detection, intelligent construction and displacement monitoring.

(3) At present, the application of 3D data will focus on the structural reconstruction and component segmentation of 3D scanning data. Lu *et al.* [150] proposed a very promising multi disaster simulation framework for CIM which needs to be improved.

(4) Many researchers have also carried out the development of intelligent detection equipment, including tunnel inspection robot, wall climbing UAV, circular wall climbing robot system ant other robot systems. They also combine the robot and intelligent detection algorithm to realize the automatic detection of the structures.

Compared with traditional manual detection methods, deep learning technology has many advantages. (1) Avoid complex data preprocessing of health monitoring signals. Deep learning can automatically complete data cleaning and data analysis, reducing manual operation. (2) It can be combined with intelligent equipment to realize automatic detection of disease. Reduce the detection blind area, reduce the human cost of detection, improve the detection efficiency and intelligent level. (3) It can be used in construction sites to promote intelligent construction and ensure the safety of workers.

This paper also summarizes some promising and less current research directions and puts forward some feasible research plans. It is recommended that further research be undertaken in the following areas. The main research directions include fine fuzzy crack detection, small sample problem, cable force measurement based on deep learning, automatic detection of underwater structure defects, automatic segmentation and reconstruction of large-scale complex surface structure, digital twin and unmanned ship equipment research and development.

This paper aims to provide reference for researchers in this field and promote the further development of related fields.

Deep learning is a rare, popular and emerging field. At the same time, Chinese people can participate in the whole process from birth, development to maturity. However, in other fields, due to various reasons, Chinese scholars start slowly and often join them in their mature period. Therefore, some scholars who have done pioneering work rarely have

Chinese names. Take civil engineering as an example: Chopra and Clough for structural dynamics, Victor Li for ECC, and H. Adeli for computer-aided engineering.

It is hoped that Chinese scholars can also make more original and subversive achievements in the cross field of deep learning and civil engineering. To make contributions from China to the development of disciplines and the progress of human civilization. Some people compare scientific research to big trees, with first-class scholars expanding trunk, second-class scholars tracking branches, and third-class scholars repeating leaves. I hope more first-class scholars can emerge in China!

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

Firstly, the author would like to extend his special thanks to Prof. Zhongwen Zhang, Prof. Yiming Yao, Prof. Ling Qiao, Prof. Qian Zhu, Prof. Lei Zhu, Prof. Xing Li for them teaching, attention and selfless assistance in the past semester. Additionally, the author really appreciate the help provided by Dr. Ni. Finally, the author also would like to gratefully acknowledge Prof. Jian Zhang for his selfless advice.

References

[1] A. L. Samuel, "Some studies in machine learning using the game of checkers," *IBM Journal of Research and Development*, vol. 3, no. 3, pp. 535–554, 1959.

[2] Q. Kong. D. T. Trugman, Z. E. Ross, M. Bianco, B. Meade, and P. Gerstoft, "Machine learning in seismology: Turning data into insights," *Seismological Research Letters*, vol. 90, no. 1, pp. 3–14, 2018.

[3] Y. Xie, M. E, and M. E. Sichani,and J. E. Padgett, and R. DesRoches, "The promise of implementing machine learning in earthquake engineering: A state-of-the-art review," *Earthquake Spectra*, Online Version of Record, 2020, DOI: 10.1177/8755293020919419

[4] H. Adeli, "Neural networks in civil engineering: 1989-2000," *Computer-Aided Civil and Infrastructure Engineering*, vol. 16, no. 2, pp. 126–142, 2001.

[5] J. Zhang, T. Sato, S. Iai, and T. Hutchinson, "A pattern recognition technique for structural identification using observed vibration signals: Linear case studies," *Engineering Structures*, vol. 30, pp. 1439–1446, 2008.

[6] J. P. Amezquita-Sanchez, M. Valtierra-Rodriguez, M. Aldwaik, and H. Adeli, "Neurocomputing in civil infrastructure," *Scientia Iranica*, vol. 23, no. 6, pp. 2417–2428, 2016.

[7] M.H. Rafiei, H. Adeli, "A novel machine learning-based algorithm to detect damage in high-rise building structures, " *The Structural Design of Tall and Special Buildings*, vol. 26, no. 18, e1400, 2017, doi:10.1002/tal.1400.

[8] W. B. Chaabene, M. F. Moncef, and L. Nehdi, "Machine learning prediction of mechanical properties of concrete: Critical review," *Construction and Building Materials*, vol. 260, 119889, 2020, doi: 10.1016/j.conbuildma-t.2020.119889

[9] K. Yan, H. Xu, G. Shen, and P. Liu, "Prediction of splitting tensile strength from cylinder compressive strength of concrete by support vector machine," *Advances in Materials Science and Engineering*, vol. 21, pp. 1937–1945 2012, doi:10.1155/2013/597257.

[10] J. Xu, X. Zhao, Y. Yu, T. Xie, G. Yang, and J. Xue, "Parametric sensitivity analysis and modelling of mechanical properties of normal- and high-strength recycled aggregate concrete using grey

theory, multiple nonlinear regression and artificial neural networks," *Construction and Building Materials*, vol. 211, no. 30, pp. 479–491, 2019, doi: 10.1016/j.conbuildmat.2019.03.234.

[11] M. Sonebi, A. Cevik, S. Grünewald, and J. Walraven, "Modelling the fresh properties of self-compacting concrete using support vector machine approach," *Construction and Building Materials*, vol. 106, no. 1, pp. 55-64, 2016, doi: 10.1016/j.conbuildmat. 2015.12.035.

[12] D. V. Dao, H. B. Ly, S.H. Trinh, T. T. Le, and B. T. Pham, "Artificial intelligence approaches for prediction of compressive strength of geopolymer concrete," *Materials (Basel)*, vol. 12, 2019, doi: 10.3390/ma12060983.

[13] O. B. Douma, B. Boukhatem, M. Ghrici, and A. Tagnit-Hamou, "Prediction of properties of self-compacting concrete containing fly ash using artificial neural network," *Neural Comput. Appl*, vol. 28, pp. 707–718, 2017, doi: 10.1007/s00521-016-2368-7.

[14] S. Lee, C. Lee, "Prediction of shear strength of FRP-reinforced concrete flexural members without stirrups using artificial neural networks," *Engineering Structures*, vol. 61, pp. 99–112, 2014, doi:10.1016/j.engstruct.2014.01.001.

[15] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, vol. 521, pp. 436-444, 2015, doi: dx.doi.org/10.1038/nature14539

[16] D. Michie, D. J. Spiegelhalter, and C. C. Taylor, "Machine learning, neural and statistical classification," New York: Ellis Horwood, 1994

[17] X. Yao, "Evolving artificial neural networks," Proceedings of the IEEE, vol. 87, no. 9, pp. 1423-1447, 1999.

[18] D. Silver, A. Huang, and C. Maddison, "Mastering the game of Go with deep neural networks and tree search," *Nature*, vol. 529, pp. 484–489, 2016, doi: 10.1038/nature16961

[19] D. Silver, J. Schrittwieser, and K. Simonyan, "Mastering the game of Go without human knowledge," *Nature*, vol. 550, pp. 354–359, 2017, doi: 10.1038/nature24270

[20] Y. Jia, E. Shelhamer, J. Donahue, J, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell, "Caffe: Convolutional architecture for fast feature embedding,". In *Proceedings of the 22nd ACM international conference on Multimedia*, New York, NY, USA, pp. 675–678, 2014.

[21] T. Chen, L. Mu, and Y. Li, "MXNet: A Flexible and Efficient Machine Learning Library for Heterogeneous Distributed Systems," *arXiv preprint arXiv: 1512.01274*, 2015

[22] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, "Tensorflow: A system for large-scale machine learning," *In Proceedings of the OSDI, Savannah*, GA, USA, 2016, pp. 265–283.

[23] A. Paszke, S. Gross, and F. Massa, "PyTorch: An Imperative Style, High-Performance Deep Learning Library," *arXiv preprint arXiv: 1912.01703*, 2019

[24] B. Alipanahi, A. Delong, M. T. Weirauch, and B. J. Frey, "Predicting the se-quence specificity of DNA-and RNA-binding proteins by deep learning," *Nature biotechnology*, vol. 33, pp. 831–838, 2015.

[25] G. Ros, L. Sellart, J. Materzynska, D. Vazquez, and A. M. Lopez, "The SYNTHIA Dataset: A Large Collection of Synthetic Images for Semantic Segmentation of Urban Scenes," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Las Vegas, NV, pp. 3234-3243, 2016, doi: 10.1109/CVPR.2016.352.

[26] D. George, and E. A. Huertab, "Deep Learning for real-time gravitational wave detection and parameter estimation: Results with Advanced LIGO data," *Physics Letters B*, vol. 778, no. 10, pp. 64-70, 2018

[27] K. T. Butler, D. W. Davies, and H. Cartwright, "Machine learning for molecular and materials science," *Nature*, vol. 559, pp. 547–555, 2018,

doi: 10.1038/s41586-018-0337-2

[28] O. Avci, O. Abdeljaber, and S. Kiranyaz, A "Review of Vibration-Based Damage Detection in Civil Structures: From Traditional Methods to Machine Learning and Deep Learning Applications," *arXiv preprint arXiv: 1912.01703*, 2004.

[29] M. Azimi, A. D. Eslamlou, and G. Pekcan, "Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review," *Sensors*, vol. 20, no. 10, pp. 2778-2811, 2020, doi:10.3390/s20102778

[30] E. Cosenza, and G. Manfredi, "Damage indices and damage measures," *Prog. Struct. Eng. Mater.* 2000, doi:10.1002/(sici)1528- 2716(200001/03) 2:1<50::aid-pse7>3.3.co;2-j.

[31] D.M. Frangopol, and J.P. Curley, "Effects of damage and redundancy on structural reliability", *Journal of Structural Engineering*, 1987, doi:10.1061/(ASCE)07339445(1987)113:7(153).

[32] K. He, and W.D. Zhu, "Structural damage detection using changes in natural frequencies: Theory and applications", *J. Phys. Conf. Ser.*, 2011. doi:10.1088/1742-6596/305/1/012054.

[33] B. Kostic, and M. Gül, "Vibration-Based Damage Detection of Bridges under Varying Temperature Effects Using Time-Series Analysis and Artificial Neural Networks", *J. Bridg. Eng*, 2017, doi:10.1061/(ASCE)BE.1943-5592.0001085.

[34] V. Meruane, and W. Heylen, "Structural damage assessment under varying temperature conditions," *Structural Health Monitoring*, 2012, doi:10.1177/1475921711419995.

[35] F. Seguel, and V. Meruane, "Damage assessment in a sandwich panel based on full-field vibration measurements," *Journal of Sound and Vibration*, 2018, doi:10.1016/j.jsv.2017.11.048.

[36] Y.J. Cha, and O. Buyukozturk, "Structural damage detection using modal strain energy and hybrid multi-objective optimization," *Computer-Aided Civil and Infrastructure Engineering*, 2015, doi:10.1111/mice.12122

[37] F. Magalhães, A. Cunha, and E. Caetano, "Vibration based structural health monitoring of an arch bridge: From automated OMA to damage detection," *Mechanical Systems and Signal Processing*, 2012, doi:10.1016/j.ymssp.2011.06.011.

[38] J.P. Amezquita-Sanchez, and H. Adeli, "Signal Processing Techniques for Vibration-Based Health Monitoring of Smart Structures", *Arch. Comput. Methods Eng.*, 2016, doi:10.1007/s11831-014-9135-7.

[39] A. Diez, N.L.D. Khoa, M. Makki Alamdari, Y. Wang, F. Chen, and P. Runcie, "A clustering approach for structural health monitoring on bridges", *J. Civ. Struct. Heal. Monit.*, 2016, doi:10.1007/s13349-016-0160-0

[40] O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, and D.J. Inman, "Wireless and Real-Time Structural Damage Detection: A Novel Decentralized Method for Wireless Sensor Networks", *Journal of Sound and Vibration*, 2018.

[41] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mechanical Systems and Signal Processing*, 2006, doi:10.1016/j.ymssp.2005.09.012.

[42] M.S. Kan, A.C.C. Tan, and J. Mathew, "A review on prognostic techniques for non-stationary and non-linear rotating systems,",4 *Mechanical Systems and Signal Processing*, 2015,doi:10.1016/j.ymssp.2015.02.016.

[43] O. Abdeljaber, S. Sassi, O. Avci, S. Kiranyaz, I. Abulrahman, and M. Gabbouj, "Fault Detection and Severity Identification of Ball Bearings by Online Condition Monitoring," *IEEE Transactions on Industrial Electronics*, 2018.

[44] R. Liu, B. Yang, E. Zio, and X. Chen, "Artificial intelligence for fault diagnosis of rotating machinery: A review", *Mechanical Systems and Signal Processing*, 2018, doi:10.1016/j.ymssp.2018.02. 016.

[45] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R.X. Gao, "Deep learning and its applications to machine health monitoring", *Mechanical Systems and Signal Processing*, 2019, doi:10.1016/j.ymssp.2018.05.050.

[46] W. Zhang, C. Li, G. Peng, Y. Chen, and Z. Zhang, "A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load," *Mechanical Systems and Signal Processing*, 2018, doi:10.1016/j.ymssp.2017.06.022.

[47] T. Ince, S. Kiranyaz, L. Eren, M. Askar, and M. Gabbouj, "Real-Time Motor Fault Detection by 1-D Convolutional Neural Networks," I*EEE Transactions on Industrial Electronics*, 2016, doi:10.1109/TIE. 2016.2582729.

[48] R. P. Bandara, T. H. T. Chan, and D. P. Thambiratnam, "Frequency response function based damage identification using principal component analysis and pattern recognition technique," *Engineering Structures*, 2014, doi:10.1016/j.engstruct.2014.01.044.

[49] R. T. Wu, and M. R. Jahanshahi, "Data fusion approaches for structural health monitoring and system identification: Past, present, and future," *Structural Health Monitoring*, 2018, doi:10.1177/1475921718798769.

[50] R. Yao, and S.N. Pakzad, "Autoregressive statistical pattern recognition algorithms for damage detection in civil structures", *Mechanical Systems and Signal Processing*, 2012, doi:10.1016/j.ymssp.2012.02.014.

[51] S. Park, C.B. Yun, Y. Roh, and J. J. Lee, "PZT-based active damage detection techniques for steel bridge components", *Smart Materials and Structures*, 2006, doi:10.1088/09641726/15/4/009.

[52] F. T. Ni, J. Zhang, and Z. Chen, "Pixel-level crack delineation in images with convolutional feature fusion," *Structural Control and Health Monitoring*, vol. 26, e2286, 2019, doi: 10.1002/stc.2286.

[53] F. T. Ni, J. Zhang, and Z. Chen, "Zernike-moment measurement of thin-crack width in images enabled by dual-scale deep learning," *Computer-Aided Civil and Infrastructure Engineering*, vol. 34, no. 5, pp. 367-384, 2019, doi: 10.1111/mice.12421.

[54] S. Jiang, and J. Zhang. "Real-time crack assessment using deep neural networks with wall climbing unmanned aerial system," *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, no. 12, pp. 549-564, 2020, doi: 10.1111/mice.12519.

[55] Y. D. Tian, C. Zhang, S. Jiang, J. Zhang, and W. H. Duan, "Noncontact Cable Force Measurement with Unmanned Aerial Vehicle and Computer Vision," *Computer-Aided Civil and Infrastructure Engineering*, In Press.

[56] W. J. Zhao, G. W. Zhang, and J. Zhang, "Cable force estimation of a long-span cable-stayed bridge with micro wave interferometric radar," *Computer-Aided Civil and Infrastructure Engineering*, Online Version of Record, 2020, doi: 10.1111/mice.12557.

[57] V. Vapnik, "Statistical Learning Theory. 1st ed," New York: John Wiley & Sons, 1998.

[58] C. M. Bishop, "Pattern Recognition and Machine Learning (ed M. Jordan, J. Kleinberg and B. Scholkopf)," New York: Springer, 2006.

[59] K. P. Murphy, "Machine Learning: A Probabilistic Perspective. Chance Encounters: Probability in Education," Cambridge, MA; London: The MIT Press, 2012.

[60] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Las Vegas, NV, pp. 770-778, 2016, doi: 10.1109/CVPR.2016.90.

[61] A. Krizhevsky, I. Sutskever, G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in Neural*

Information Processing Systems (*NeurIPS*), pp. 1097-1105, 2012.

[62] C. Szegedy, W. Liu, and Y. Jia Y, "Going deeper with convolutions," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), pp. 1-9, 2015.

[63] K. Simonyan, A. Zisserman, "Very deep convolutional networks for large-scale image recognition" [J]. arXiv preprint arXiv:1409.1556, 2014.

[64] S. Xie, R. Girshick, and P. Dollár, "Aggregated residual transformations for deep neural networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), pp. 1492-1500, 2017.

[65] G. Huang, Z. Liu, L. V. Maaten, Q. Kilian, "Densely connected convolutional networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), pp. 4700-4708, 2017.

[66] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), pp. 7132-7141, 2018.

[67] W. Sanghyun, P. Jongchan, and J. Y. Lee, "CBAM: Convolutional Block Attention Module," *arXiv preprint arXiv: 1807.06521*, 2018.

[68] Z. Gao, J. Xie, and Q. Wang, "Global Second-order Pooling Convolutional Networks," *arXiv preprint arXiv: 1811.12006*, 2018.

[69] I. Bello, B. Zoph, and A. Vaswani, "Attention Augmented Convolutional Networks," *arXiv preprint arXiv: 1904.09925*, 2019.

[70] H. Zhang, C. Wu, and Z. Zhang, "ResNeSt: Split-Attention Networks," *arXiv preprint arXiv: 2004.08955*, 2020.

[71] R. Girshick, J. Donahue, and T. Darrell, Rich "Feature hierarchies for accurate object detection and semantic segmentation" in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), pp. 580-587, 2014.

[72] R. Girshick, "Fast R-CNN," in *Proceedings of the IEEE International Conference on Computer Vision* (*ICCV*), pp. 1440-1448. 2015.

[73] S. Ren, K. He, and R. Girshick R, "Faster R-CNN: Towards real-time object detection with region proposal networks," in *Advances in Neural Information Processing Systems* (*NeurIPS*), pp. 91-99, 2015.

[74] J. Redmon, S. Divvala, and R. Girshick, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), pp. 779-788, 2016.

[75] W. Liu, D. Anguelov, and D. Erhan, "SSD: Single shot multibox detector," in *European Conference on Computer Vision* (*ECCV*), Springer, Cham, pp. 21-37, 2016.

[76] J. Redmon, A. Farhadi, "YOLO9000: Better, Faster, Stronger," *arXiv preprint arXiv: 1612.08242*, 2016.

[77] J. Redmon, A. Farhadi, "YOLOv3:An Incremental Improvement," *arXiv preprint arXiv: 1804.02767*, 2018

[78] A. Bochkovskiy, C. Y. Wang, and H. Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," *arXiv preprint arXiv: 2004.10934*, 2020.

[79] J. Long, E. Shelhamer and T. Darrell, "Fully convolutional networks for semantic segmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Boston, MA, 2015, pp. 3431-3440, doi: 10.1109/CVPR. 2015.7298965.

[80] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Medical Image Computing and Computer-Assisted Intervention* (*MICCAI*), pp. 234–241, 2015.

[81] K. He, G. Gkioxari, and P. Dollár, "Mask R-CNN," in *Proceedings of the IEEE International Conference on Computer Vision* (*ICCV*), pp. 2961-2969, 2017.

[82] M. X. Tan, R. M. Pang, and Q. V. Le, "EfficientDet: Scalable and Efficient Object Detection," *arXiv preprint arXiv: 1911.09070*, 2019.

[83] M. X. Tan, Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," *arXiv preprint arXiv: 1905.11946*, 2019.

[84] T. Qin, K. Wu, and D. Xiu, "Data driven governing equations approximation using deep neural networks," *Journal of Computational Physics*, vol. 395, pp. 620 – 635, 2019.

[85] S. Pawar, S. M. Rahman, H. V addireddy, O. San, A. Rasheed, and P. Vedula, "A deep learning enabler for nonintrusive reduced order modeling of fluid flows," *Physics of Fluids*, vol. 31, 085101, 2019.

[86] Z. Long, Y. Lu, X. Ma, and B. Dong, "PDE-net: Learning PDEs from data," in *Proceedings of the 35th International Conference on Machine Learning* (*PMLR*), vol. 80, pp. 3208–3216, 2018.

[87] Z. Long, Y. Lu, and B. Dong, PDE-Net 2.0: "Learning PDEs from data with a numeric-symbolic hybrid deep network," *Journal of Computational Physics*, vol. 399, 108925, 2019.

[88] M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics Informed Deep Learning (Part I): Data-driven Solutions of Nonlinear Partial Differential Equations," *arXiv preprint arXiv: 1711.10561*, 2017.

[89] M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics Informed Deep Learning (Part II): Data-driven Discovery of Nonlinear Partial Differential Equations," *arXiv preprint arXiv: 1711.10566*, 2017.

[90] M. Raissi, G. E. Karniadakis, "Hidden physics models: Machine learning of nonlinear partial differential equations," *Journal of Computational Physics*, vol. 357, pp. 125–141, 2018.

[91] M. Raissi, A. Yazdani, and G. E. Karniadakis, "Hidden fluid mechanics: Learning velocity and pressure fields from flow visualizations," *Science*, vol. 367, pp. 1026–1030, 2020.

[92] E. Haghighata, M. Raissib, A. Mourec, H. Gomezc, and R. Juanesa, "A deep learning framework for solution and discovery in solid mechanics: linear elasticity," *arXiv preprint arXiv: 2003.02751*, 2020.

[93] M. T. Rad, A. Viardin, G.J. Schmitz, and M. Apel, "Theory-training deep neural networks for an alloy solidification benchmark problem," *Computational Materials Science*, vol. 180, 109687, 2020.

[94] Y. J. Shin, J. Darbon, and G. E. Karniadakis, "Convergence and Generalisation of Physics Informed Neural Networks," *arXiv preprint arXiv: 2004.01806*, 2020.

[95] S. Z. Wu, C. Rupprecht, and A. Vedaldi, "Unsupervised Learning of Probably Symmetric Deformable 3D Objects from Images in the Wil d," *arXiv preprint arXiv: 1911.11130*, 2019.

[96] Z. Chen, A. Tagliasacchi, and H. Zhang, "BSP-Net: Generating Compact Meshes via Binary Space Partitioning," *arXiv preprint arXiv: 1911.06971*, 2019.

[97] C. R. Qi, H. Su, and K. Mo, "PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation," *arXiv preprint arXiv: 1612.00593*, 2016.

[98] C. R. Qi, L. Yi, and H. Su, "LeonidasJ.Guibas, PointNet++: Deep Hierarchical Feature Learning on Point Setsina Metric Space," *arXiv preprint arXiv: 1706.02413*, 2017.

[99] Y. Ben-Shabat, M. Lindenbaum, and A. Fischer, "Nesti-Net: Normal Estimation for Unstructured 3D Point Clouds," *arXiv preprint arXiv: 1812.00709*, 2018.

[100] A. Komarichev, Z. Zhong, and J. Hua, "A-CNN: Annularly Convolutional Neural Networks on Point Clouds, " *arXiv preprint arXiv: 1904.08017*, 2019.

[101] Y. Wang, Y. Sun, and Z. Liu, "Dynamic Graph CNN for Learning on Point Clouds," *arXiv preprint arXiv: 1801.07829*, 2018.

[102] A. Mohan, and S. Poobal, "Crack detection using image processing: A critical review and analysis," *Alex. Eng. J.* vol. 57, pp. 787–798, 2018.

[103] Elsken, Thomas, J. H. Metzen, and F. Hutter. "Neural Architecture Search: A Survey," *Journal of Machine Learning Research*, vol. 20, no. 55, pp. 1-21, 2019.

[104] B. K. Oh, Y. J. Park, and H. S. Park, "Seismic response prediction method for building structures using convolutional neural network," *Structural Control and Health Monitoring*, vol. 27, e2519, 2020.

[105] B. K. Oh, B. Glisica, and S. Wook Park, "Neural network-based seismic response prediction model for building structures using artificial earthquakes," *Journal of Sound and Vibration*, vol. 468, 115109, 2020.

[106] R. Zhang, Z. Chen, and H. Sun, "Deep long short-term memory networks for nonlinear structural seismic response prediction," *Computers and Structures*, vol. 220, pp. 55-68, 2019.

[107] R. Zhang, Y. Liu, and H. Sun, "Physics-guided convolutional neural network (PhyCNN) for data-driven seismic response modeling," *Engineering Structures*, vol. 215,110704, 2020.

[108] R. Zhang, Y. Liu, and H. Sun, "Physics-Informed Multi-LSTM Networks for Metamodeling of Nonlinear Structures," *arXiv preprint arXiv: 2002.10253*, 2020.

[109] B. K. Oh, B.Glisic, and Y. Kim, "Convolutional neural network-based wind-induced response estimation model for tall buildings," *Computer-Aided Civil and Infrastructure Engineering*, vol. 34, pp. 843–858, 2019.

[110] G. Fan, J. Li, and H. Hao, "Dynamic response reconstruction for structural health monitoring using densely connected convolutional networks," *Structural Health Monitoring*, Online Version of Record, 2020.

[111] S. O. Sajedi, and X. Liang, "Vibration-based semantic damage segmentation for large-scale structural health monitoring," *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, pp. 579–596, 2020.

[112] S. O. Sajedi, and X. Liang, "A datadriven framework for near real-time and robust damage diagnosis of building structures, " *Structural Control and Health Monitoring*, vol. 27, e2488, 2020.

[113] R. Wang, J. Li, and H. Hao, "Deep residual network framework for structural health monitoring, " *Structural Health Monitoring*, 2020, In press.

[114] Z. Ding, J. Li, and H. Hao, "Structural damage identification by sparse deep belief network using uncertain and limited data," *Structural Control and Health Monitoring*, vol. 27, e2522, 2020.

[115] Y. Zhang, Y. Miyamori, and S. Mikami, "Vibration-based structural state identification by a 1-dimensional convolutional neural network, " *Computer-Aided Civil and Infrastructure Engineering* vol. 34, pp. 822–839, 2019.

[116] M. Azimi, and G. Pekcan, "Structural health monitoring using extremely compressed data through deep learning," *Computer-Aided Civil and Infrastructure Engineering*. vol. 35, pp. 597-614, 2020.

[117] Gao Fan, J. Li, and H. Hao, "Vibration signal denoising for structural health monitoring by residual convolutional neural networks," *Measurement*, vol. 157, 107651, 2020

[118] Gao Fan, J. Li, and H. Hao, "Lost data recovery for structural health monitoring based on convolutional neural networks," *Structural Control and Health Monitoring*, vol. 26, e2433, 2019.

[119] Z. Tang, Y. Bao, and H. Li, "Group sparsity-aware convolutional neural network for continuous missing data recovery of structural health monitoring," *Structural Control and Health Monitoring*, Online Version of Record, 2020.

[120] Z. Tang, Z. Chen, and H. Li, "Convolutional neural network - based data anomaly detection method using multiple information for structural health monitoring," *Structural Control and Health Monitoring*, vol. 26, e2296, 2019.

[121] F. T. Ni, J. Zhang, and M. N. Noori, "Deep learning for data anomaly detection and data compression of a long-span suspension bridge, " *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, pp. 685–700, 2020.

[122] Y. Fujita, Y. Mitani, and Y. Hamamoto, "A method for crack detection on a concrete structure," in *18th International Conference on Pattern Recognition (ICPR)*, Hong Kong, pp. 901-904, 2006.

[123] H. Oliveira and P. L. Correia, "Automatic road crack segmentation using entropy and image dynamic thresholding," in *17th European Signal Processing Conference (ESPC)*, Glasgow, pp. 622-626, 2009.

[124] T. Yamaguchi, S. Nakamura, R. Saegusa, and S. Hashimoto, "Image-based crack detection for real concrete surfaces," *IEEJ Transactions on Electrical and Electron Engineering*, vol. 3, no. 1, pp. 128–135, 2008, doi: 10.1002/tee.20244.

[125] Y. J. Cha, W.ooram Choi, and O. Büyüköztürk, "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks," *Computer-Aided Civil and Infrastructure Engineering*, vol. 32, pp. 361–378, 2017.

[126] Y. Z. Lin, Z. H. Nie, and H. W. Ma, "Structural Damage Detection with Automatic Feature-Extraction through Deep Learning, " *Computer-Aided Civil and Infrastructure Engineering*, vol. 32, pp. 1025–1046, 2017.

[127] X. C. Yang, H. Li, and Y. T. Yu, "Automatic Pixel-Level Crack Detection and Measurement Using Fully Convolutional Network, " *Computer-Aided Civil and Infrastructure Engineering*. vol. 33, pp. 1090–1109, 2018.

[128] X. Liang, "Image-based post-disaster inspection of reinforced concrete bridge systems using deep learning with Bayesian optimization," *Computer-Aided Civil and Infrastructure Engineering*, vol. 34, pp. 415–430, 2019.

[129] X. X. Zhang, D. Rajan, and B. Story, "Concrete crack detection using context-aware deep semantic segmentation network," *Computer-Aided Civil and Infrastructure Engineering*, vol. 34, pp. 951–971, 2019, doi: 10.1111/mice.12477

[130] Q. P. Mei, M. Gül, and M. R. Azim, "Densely connected deep neural network considering connectivity of pixels for automatic crack detection," *Automation in Construction*, vol. 110, 103018, 2020

[131] Q. P. Mei, and M. Gül, "Multi-level feature fusion in densely connected deep-learning architecture and depth-first search for crack segmentation on images collected with smartphones," *Structural Control and Health Monitoring*, Online Version of Record, 2020, doi: 10.1177/1475921719896813

[132] W. Choi, and Y. J. Cha, "SDDNet: Real-Time Crack Segmentation," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 9, 2020

[133] D. Kanga, S. S. Benipala, and Y. J. Cha, "Hybrid pixel-level concrete crack segmentation and quantification across complex backgrounds using deep learning," *Automation in Construction*, vol. 118, 103291, 2020.

[134] Z. Tong, J. Gao, and A. Sha, "Convolutional Neural Network for Asphalt Pavement Surface Texture Analysis," *Computer-Aided Civil and Infrastructure Engineering*, vol. 33, pp. 1056–1072, 2018.

[135] H. Maeda, Y. Sekimoto, and T. Seto, "Road Damage Detection and Classification Using Deep Neural Networks with Smartphone Images," *Computer-Aided Civil and Infrastructure Engineering*. vol. 33, pp. 1127–1141, 2018.

[136] A. Zhang, C. P. Kelvin, and Y. F. Wang, "Automated Pixel-Level Pavement Crack Detection on 3D Asphalt Surfaces with a

Recurrent Neural Network," *Computer-Aided Civil and Infrastructure Engineering*, vol. 34 pp. 213–229, 2019.

[137] Z. Tong, D. D. Yuan, and J. Gao, "Pavement defect detection with fully convolutional network and an uncertainty framework, " *Computer-Aided Civil and Infrastructure Engineering*, Online Version of Record, 2020.

[138] Q. P. Mei, and M. Gül, "A cost effective solution for pavement crack inspection using cameras and deep neural networks," *Construction and Building Materials*, vol. 256, 119397, 2020.

[139] H. Maeda, T. Kashiyama, and Y. Sekimoto, "Generative adversarial network for road damage detection," *Computer-Aided Civil and Infrastructure Engineering*, Online Version of Record, 2020.

[140] S. Y. Li, X. F. Zhao, and G.Y. Zhou, "Automatic pixel-level multiple damage detection of concrete structure using fully convolutional network," *Computer-Aided Civil and Infrastructure Engineering*, vol. 34, pp. 616–634, 2019.

[141] Y. Xu, Y. Q. Bao, and H. Li, "Automatic seismic damage identification of reinforced concrete columns from images by a region - based deep convolutional neural network," *Structural Control and Health Monitoring*, vol. 26, e2313, 2019.

[142] C. Zhang, C. C. Chang, and M. Jamshidi, "Concrete bridge surface damage detection using a single-stage detector, " *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, pp. 389–409, 2020.

[143] R. Ali, and Y. J. Cha, "Subsurface damage detection of a steel bridge using deep learning and uncooled micro-bolometer," *Construction and Building Materials*, vol. 226, pp. 376–387, 2019.

[144] X. F. Zhao, Y. Zhang, and N. N. Wang, "Bolt loosening angle detection technology using deep learning, " *Structural Control and Health Monitoring*, vol. 26, e2292, 2019.

[145] H. C. Pham, Q. B. Ta, and J. T. Kim, "Bolt-Loosening Monitoring Framework Using an Image-Based Deep Learning and Graphical Model," *Sensors*, vol. 20, no. 3382, 2020, doi:10.3390/s20123382

[146] N. Wang, X. Zhao, and Z. Zou, "Autonomous damage segmentation and measurement of glazed tiles in historic buildings via deep learning," *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, pp. 277–291, 2020.

[147] S. Arabi, A. Haghighat, and A. Sharma, "A deep-learning-based computer vision solution for construction vehicle detection, " *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, pp. 753–767, 2020.

[148] J. Shen, X. Xiong, and Y. Li, "Detecting safety helmet wearing on construction sites with bounding-box regression and deep transfer learning," *Computer-Aided Civil and Infrastructure Engineering*, Online Version of Record, 2020.

[149] Y. Zhang, X. Zhao and P. Liu, "Multi-Point Displacement Monitoring Based on Full Convolutional Neural Network and Smartphone," *IEEE Access*, vol. 7, pp. 139628-139634, 2019, doi: 10.1109/ACCESS.2019. 2943599.

[150] X. Z. Lu, D. L. Gu, and Z. Xu, "CIM-Powered Multi-Hazard Simulation Framework Covering both Individual Buildings and Urban Areas, " *Sustainability*, vol. 12, no. 5059, pp. 1-28, 2020 doi:10.3390/su12125059

[151] R. Lu, I. Brilakis, and C. R. Middleton, "Detection of Structural Components in Point Clouds of Existing RC Bridges," *Computer-Aided Civil and Infrastructure Engineering*, vol. 34, pp. 191–212, 2019.

[152] Y. F. Liu, X. Nie, and J. S. Fan, "Image-based crack assessment of bridge piers using unmanned aerial vehicles and three-dimensional scene reconstruction," *Computer-Aided Civil and*

Infrastructure Engineering, vol. 35, pp. 511–529, 2019.

[153] S. Shi, C. Guo, and L. Jiang, "PV-RCNN: Point-Voxel Feature Set Abstraction for 3D Object Detection," *arXiv preprint arXiv: 1912.13192*, 2019.

[154] Q. Xu, X. Sun, C. Y. Wu, "Grid-GCN for Fast and Scalable Point Cloud Learning," *arXiv preprint arXiv: 1912.02984*, 2019.

[155] H. Kim, J. Yoon, and S. H. Sim, "Automated bridge component recognition from point clouds using deep learning," *Structural Control and Health Monitoring*, e2591, 2020.

[156] F. Hu. J. Zhao, and H. Li, "Structure-aware 3D reconstruction for cable-stayed bridges: A learning-based method," *Computer-Aided Civil and Infrastructure Engineering*. Online Version of Record, 2020.

[157] Y. Xue, Y. Li, "A Fast Detection Method via Region-Based Fully Convolutional Neural Networks for Shield Tunnel Lining Defects," *Computer-Aided Civil and Infrastructure Engineering*, vol. 33, pp. 638–654, 2018.

[158] H. Huang, Q. Li, and D. Zhang, "Deep learning based image recognition for crack and leakage defects of metro shield tunnel," *Tunnelling and Underground Space Technology*, vol. 77, pp. 166-176, 2018.

[159] E. Menendez, J. G. Victores, and R. Montero, "Tunnel structural inspection and assessment using an autonomous robotic system," *Automation in Construction*, vol. 87, pp. 117-126, 2020.

[160] N. Metni, and T. Hamel, "A UAV for bridge inspection: visual servoing control law with orientation limits," *Automation in Construction*, vol. 17, no. 1, pp. 3-10, 2007, doi: 10.1016/ j.autcon.2006.12.010.

[161] W. Yi, and M. Sutrisna, "Drone scheduling for construction site surveillance," *Computer-Aided Civil and Infrastructure Engineering*, Online Version of Record, 2020.

[162] H. M. La, N. Gucunski, K. Dana, and S. H. Kee, "Development of an autonomous bridge deck inspection robotic system," *Journal of Field Robotics*, vol. 34, no. 8, pp. 1489-1504, 2017.

[163] S. Gibb, H. M. La, T. Le, N. R. Schmid, and H. Pham, "Nondestructive evaluation sensor fusion with autonomous robotic system for civil infrastructure inspection," *Journal of Field Robotics*, vol. 35, no. 6, pp. 988–1004, 2018.

[164] X. Li, C. Gao,Y. Guo, F. He, and Y. Shao, "Cable surface damage detection in cable-stayed bridges using optical techniques and image mosaicking," *Optics and Laser Technology*, vol. 110, pp. 36–43, 2019.

[165] K. Jang, Y. K. An, and B.Kim, "Automated crack evaluation of a high-rise bridge pier using aring-type climbing robot," *Computer-Aided Civil and Infrastructure Engineering*, Online Version of Record, 2020.

[166] L. Pauline, C. Camille, and C. Soumith, "Semantic Segmentation using Adversarial Networks," *arXiv preprint arXiv:1611.08408*, 2016.

[167] Y. F. Liu, K. Chen, and Z. C. Qin, "Structured Knowledge Distillation for Semantic Segmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), pp. 2604-2613, 2019.

[168] J. Guo, Q. Wang, and Y. Li, "Façade defects classification from imbalanced dataset using meta learning-based convolutional neural network," *Computer-Aided Civil and Infrastructure Engineering*, Online Version of Record, 2020.

[169] X. Yang, Y. Bao, H. Li, "Attribute-based structural damage identification by few-shot meta learning with inter-class knowledge transfer," *Structural Health Monitoring*, Online Version of Record, 2020.

[170] Y. Hashisho, M. Albadawi, Tom Krause, et al, "Underwater Color Restoration Using U-Net Denoising Autoencoder," *arXiv preprint arXiv:*

1905.09000, 2019.

Appendixes

Appendix A. A list of the papers I reviewed by categorizing them into different aspects

One-dimensional data					
Num	Title	Journal	Authors	Institutes	Comments
1	Seismic response prediction method for building structures using convolutional neural network	Struct Control Health Monit,2020	Byung Kwan Oh	Department of Civil and Environmental Engineering, Princeton University, Center for Structural Health Care Technology in Building, Yonsei University	
			Youngjun Park Hyo Seon Park	Department of Architectural Engineering Yonsei University	
2	Neural network-based seismic response prediction model for building structures using artificial earthquakes	Journal of Sound and Vibration,2020	Byung Kwan Oh	*the same as above*	
			Branko Glisica,	Department of Civil and Environmental Engineering, Princeton University,	
			Sang Wook Park	Architectural and Environmental Engineering, University of Texas at Austin	
3	Deep long short-term memory networks for nonlinear structural seismic response prediction	Computers and Structures 2019	Ruiyang Zhang	Department of Civil and Environmental Engineering, Northeastern University	孙皓，河海大学本科，麻省理工学院博士后，匹兹堡大学助理教授，现为美国东
			Zhao Chen	Institute of Geophysics, China Earthquake Administration, Beijing	
			Hao Sun	Department of Civil and Environmental	

				Engineering, Northeastern University Department of Civil and Environmental Engineering, MIT, Cambridge	北大学助理教授。张瑞阳，山东大学本科，马里兰大学博士，马里兰大学助理研究员，匹兹堡大学博后，现美国东北大学博后。
4	Physics-guided convolutional neural network (PhyCNN) for data-driven seismic response modeling	Engineering Structures 2020	Ruiyang Zhang	Department of Civil and Environmental Engineering, Northeastern University	
			Yang Liu	Department of Mechanical and Industrial Engineering, Northeastern University	
			Hao Sun	Department of Civil and Environmental Engineering, Northeastern University Department of Civil and Environmental Engineering, MIT, Cambridge	
5	Physics-Informed Multi-LSTM Networks for Metamodeling of Nonlinear Structures	arXiv 2020.2	Ruiyang Zhang	*the same as above*	
			Yang Liu	*the same as above*	
			Hao Sun	*the same as above*	
6	Convolutional neural network-based wind-induced response estimation model for tall buildings	Comput Aided Civ 2019	Byung Kwan Oh	*the same as above*	
			Branko Glisica,	*the same as above*	
			Yousok Kim	Department of Architectural Engineering, Hongik University	
7	Vibration-based semantic damage segmentation for large-scale structural health monitoring	Comput Aided Civ 2020	Seyed Omid Sajedi	Department of Civil, Structural and Environmental Engineering, University at Buffalo	
			Xiao Liang	Department of Civil, Structural and	

				Environmental Engineering, University at Buffalo	
8	A datadriven framework for near real - time and robust damage diagnosis of building structures	Structural control and health monitoring 2020	Seyed Omid Sajedi	*the same as above*	
			Xiao Liang	*the same as above*	
9	Structural health monitoring using extremely compressed data through deep learning	Computer-Aided Civil and Infrastructure Engineering. 2020	Mohsen Azimi Gokhan Pekcan	Department of Civil and Environmental Engineering, University of Nevada Reno, Reno, NV, USA	
10	Group sparsity-aware convolutional neural network for continuous missing data recovery of structural health monitoring	Structural Health Monitoring, 2020	Zhiyi Tang Yuequan Bao Hui Li	Key Lab of Structures Dynamic Behavior and Control of the Ministry of Education, Harbin Institute of Technology, Harbin, China School of Civil Engineering, Harbin Institute of Technology, Harbin, China	李惠，哈尔滨工业大学土木工程学院教授，长江学者，国家杰青，健康监测领域顶尖团队。2020 年发表中国土木工程领域第一篇 Science。
11	Convolutional neural network - based data anomaly detection method using multiple information for structural health monitoring	Structural control and health monitoring 2019	Zhiyi Tang Zhicheng Chen Hui Li	*the same as above*	
12	Deep residual network framework for structural health monitoring	Structural Health Monitoring, 2020	Ruhua Wang	School of Electrical Engineering, Computing and Mathematical Sciences, Curtin University, Bentley, WA, Australia	Hong Hao， 澳大利亚科廷大学杰出教授。 Li Jun，西澳大

			Jun Li Hong Hao,	Centre for Infrastructural Monitoring and Protection, School of Civil and Mechanical Engineering, Curtin University, Bentley, WA, Australia	利亚大学研究助理，现为澳大利亚科廷大学高级讲师。
13	Structural damage identification by sparse deep belief network using uncertain and limited data	Structural control and health monitoring,2020 2020	Zhenghao Ding Jun Li Hong Hao	*the same as above*	
14	Vibration signal denoising for structural health monitoring by residual convolutional neural networks	Measurement, 2020	Gao Fan Jun Li, Hong Hao	*the same as above*	
15	Lost data recovery for structural health monitoring based on convolutional neural networks	Structural control and health monitoring, 2019	Gao Fan Jun Li, Hong Hao	*the same as above*	
16	Dynamic response reconstruction for structural health monitoring using densely connected convolutional networks	Structural Health Monitoring, 2020,	Gao Fan Jun Li, Hong Hao	*the same as above*	
17	Deep learning for data anomaly detection and data compression of a long-span suspension bridge,	Computer-Aided Civil and Infrastructure Engineering. 2020	FuTao Ni Jian Zhang	School of Civil Engineering, Southeast University, Nanjing, China	张建，西安交通大学本科，日本京都大学博士，现东南大学土木工程学院副院长。CACAIE 编委。

			MohammadN.Noori	Mechanical Engineering, California Polytechnic State University, San Luis Obispo, CA, USA	Noori，曾加州州立理工大学工学院院长，美国北卡州立大学机械与航空航天系系主任，东南大学访问教授
18	Vibration-based structural state identification by a 1-dimensional convolutional neural network	Computer-Aided Civil and Infrastructure Engineering. 2020	Youqi Zhang	Department of Cold Regions, Environmental and Energy Engineering, Kitami Institute of Technology, Hokkaido, Japan	
			Yasunori Miyamori, Shuichi Mikami, Takehiko Saito	2Department of Civil and Environmental Engineering, Kitami Institute of Technology, Hokkaido, Japan	
Two-dimensional data—damage detecton (Concrete structure and pavement)					
19	Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks	Computer-Aided Civil and Infrastructure Engineering. 2017	Young-Jin Cha Wooram Choi	Department of Civil Engineering, University of Manitoba, Winnipeg, MB, Canada	Young-Jin Cha, 发表了第一篇深度学习进行裂缝检测的论文。引用次数 500+。现为加拿大曼尼
			Oral Buyukozturk	Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA, USA	

20	SDDNet: Real-Time Crack Segmentation	IEEE Transactions on Industrial Electronics, 2020	Young-Jin Cha Wooram Choi	*the same as above*	托巴大学助理教授。
21	Hybrid pixel-level concrete crack segmentation and quantification across complex backgrounds using deep learning	Automation in Construction,2020	Dongho Kanga Sukhpreet S. Benipala Wooram Choi	*the same as above*	
22	Automatic pixel-level multiple damage detection of concrete structure using fully convolutional network,	Computer-Aided Civil and Infrastructure Engineering, 2019	Shengyuan Li Xuefeng Zhao Guangyi Zhou	School of Civil Engineering, State Key Laboratory of Coastal and Offshore Engineering, Dalian University of Technology, Dalian, China	赵雪峰，大连理工大学土木工程学院教授。在该领域已经发表多篇论文。
23	Densely connected deep neural network considering connectivity of pixels for automatic crack detection	Automation in Construction, 2020	Qipei Mei Mustafa Gü Md Riasat Azim	Department of Civil and Environmental Engineering, University of Alberta, Edmonton	Qipei Mei 阿尔伯塔大学博士生，在该领域已经发表多篇文章。
24	Multi-level feature fusion in densely connected deep-learning architecture and depth-first search for crack segmentation on images collected with smartphones	Structural Health Monitoring, 2020	Qipei Mei Mustafa Gü	*the same as above*	
25	A cost effective solution for pavement crack inspection using cameras and deep neural networks	Construction and Building Materials,2020	Qipei Mei Mustafa Gü	*the same as above*	
26	Pixel-level crack delineation in images with convolutional feature fusion	Structural Control and Health	FuTao Ni Jian Zhang	*the same as above*	

		Monitoring,2019	ZhiQiang Chen	Department of Civil and Mechanical Engineering, University of Missouri-Kansas City, Kansas, Missouri, USA	
27	Zernike-moment measurement of thin-crack width in images enabled by dual-scale deep learning	Computer-Aided Civil and Infrastructure Engineering, 2020	FuTao Ni Jian Zhang ZhiQiang Chen	*the same as above*	
28	Image-based post-disaster inspection of reinforced concrete bridge systems using deep learning with Bayesian optimization	Computer-Aided Civil and Infrastructure Engineering, 2019	Xiao Liang	*the same as above*	
29	Automatic seismic damage identification of reinforced concrete columns from images by a region - based deep convolutional neural network	Structural control and health monitoring,2019	Yang Xu Yuequan Bao Hui Li	*the same as above*	
30	Structural Damage Detection with Automatic Feature-Extraction through Deep Learning	Computer-Aided Civil and Infrastructure Engineering, 2017	Yi-zhou Lin Zhen-hua Nie Hong-wei Ma	School of Mechanics and Construction Engineering, Jinan University & Key Lab of Disaster Forecast and Control in Engineering, Ministry of Education, Guangzhou, China	
31	Automatic Pixel-Level Crack Detection and Measurement Using Fully Convolutional Network	Computer-Aided Civil and Infrastructure Engineering, 2018	Xincong Yang Heng Li Yantao Yu	Department of Building and Real Estate, the Hong Kong Polytechnic University, Hung Hom, Hong Kong and School of Civil Engineering, Harbin Institute of Technology, Harbin, Heilongjiang, China	

32	Convolutional Neural Network for Asphalt Pavement Surface Texture Analysis	Computer-Aided Civil and Infrastructure Engineering, 2018	Zheng Tong Jie Gao Aimin Sha	School of Highway, Chang'an University, Xi'an, China	
33	Road Damage Detection and Classification Using Deep Neural Networks with Smartphone Images	Computer-Aided Civil and Infrastructure Engineering, 2018	Hiroya Maeda Yoshihide Sekimoto Toshikazu Seto,	Institute of Industrial Science, The University of Tokyo, Tokyo, Japan	
34	Automated Pixel-Level Pavement Crack Detection on 3D Asphalt Surfaces with a Recurrent Neural Network	Computer-Aided Civil and Infrastructure Engineering, 2019	Allen Zhang Kelvin C. P. Wang Yue Fei	School of Civil and Environmental Engineering, Oklahoma State University, OK, USA	
35	Concrete crack detection using context-aware deep semantic segmentation network	Computer-Aided Civil and Infrastructure Engineering, 2019	Xinxiang Zhang, Dinesh Rajan Brett Story,	Department of Electrical and Computer Engineering, Southern Methodist University, Dallas, TX, USA	
36	Pavement defect detection with fully convolutional network and an uncertainty framework,	Computer-Aided Civil and Infrastructure Engineering, 2020	Zheng Tong Dongdong Yuan Jie Gao	Sorbonne Université, Université de Technologie de Compiègne, CNRS, Compiègne cedex, France	
37	Generative adversarial network for road damage detection	Computer-Aided Civil and Infrastructure Engineering, 2020	Hiroya Maeda Takehiro Kashiyama Yoshihide Sekimoto	University of Tokyo, Tokyo, Japan	

38	Concrete bridge surface damage detection using a single-stage detector	Computer-Aided Civil and Infrastructure Engineering, 2020	Chaobo Zhang, Chih-chen Chang Maziar Jamshidi	Department of Civil and Environmental Engineering, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong	
Two-dimensional data—Disease detection of steel structures					
39	Subsurface damage detection of a steel bridge using deep learning and uncooled micro-bolometer	Construction and Building Materials, 2019	Rahmat Ali Young-Jin Cha	*the same as above*	
40	Bolt loosening angle detection technology using deep learning	Structural Control and Health Monitoring,2019	Xuefeng Zhao Yang Zhang Niannian Wang	*the same as above*	
41	Bolt-Loosening Monitoring Framework Using an Image-Based Deep Learning and Graphical Model	Sensors 2020	Hai Chien Pham	Applied Computational Civil and Structural Engineering Research Group, Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City 700000, Vietnam	
			Quoc-Bao Ta Jeong-Tae Kim	Ocean Engineering Department, Pukyong National University, Busan 48513, Korea	
Two-dimensional data—Disease detection of ancient buildings					
42	Autonomous damage segmentation and measurement of glazed tiles in historic buildings via deep learning	Computer-Aided Civil and Infrastructure	Niannian Wang Xuefeng Zhao Zheng Zou	*the same as above*	

		Engineering, 2020			
Two-dimensional data—Intelligent construction					
43	Detecting safety helmet wearing on construction sites with bounding-box regression and deep transfer learning	Computer-Aided Civil and Infrastructure Engineering, 2020	Jie Shen Xin Xiong Ying Li	School of Computer Science & Engineering, University of Electronic Science and Technology of China, Chengdu, China	
44	A deep-learning-based computer vision solution for construction vehicle detection	Computer-Aided Civil and Infrastructure Engineering, 2020	Saeed Arabi Arya Haghighat Anuj Sharma	Department of Civil, Construction, and Environmental Engineering, Iowa State University, Ames, Iowa	
Two-dimensional data—Other applications					
45	Multi-Point Displacement Monitoring Based on Full Convolutional Neural Network and Smartphone	IEEE Access, 2019	Yang Zhang Xuefeng. Zhao Peng Liu	*the same as above*	
Three-dimensional data					
46	CIM-Powered Multi-Hazard Simulation Framework Covering both Individual Buildings and Urban Areas	Sustainability, 2020	Xinzheng Lu Donglian Gu Zhen Xu	Key Laboratory of Civil Engineering Safety and Durability of China Education Ministry, Department of Civil Engineering, Tsinghua University, Beijing 100084, China	陆新征，清华大学土木工程系教授，长江学者，抗震工程领域专家，首届“科学

					探索奖”获得者。
47	Detection of Structural Components in Point Clouds of Existing RC Bridges	Computer-Aided Civil and Infrastructure Engineering, 2019	Ruodan Lu Ioannis Brilakis Campbell R. Middleton	Laing O’Rourke Center, Department of Engineering, University of Cambridge, Cambridge, UK	
48	Image-based crack assessment of bridge piers using unmanned aerial vehicles and three-dimensional scene reconstruction	Computer-Aided Civil and Infrastructure Engineering, 2020	Yu-Fei Liu Xin Nie Jian-Sheng Fan	Key Laboratory of Civil Engineering Safety and Durability of China Education Ministry, Department of Civil Engineering, Tsinghua University, Beijing 100084, China	刘宇飞，樊建生，清华大学土木工程系助理研究员 樊建生，清华大学土木工程系教授，钢-混凝土组合结构专家，首届“科学探索奖”获得者。
49	Automated bridge component recognition from point clouds using deep learning	Structural Control and Health Monitoring, 2020	Hyunjun Kim Jinyoung Yoon Sung-Han Sim	School of Civil, Architectural Engineering and Landscape Architecture, Sungkyunkwan University, Suwon, 16419, Republic of Korea	
50	Structure-aware 3D reconstruction for cable-stayed bridges: A learning-based method	Computer-Aided Civil and Infrastructure Engineering, 2020	Fangqiao Hu Jin Zhao Hui Li	*the same as above*	

Intelligent detection equipment					
51	A Fast Detection Method via Region-Based Fully Convolutional Neural Networks for Shield Tunnel Lining Defects	Computer-Aided Civil and Infrastructure Engineering, 2018	Yadong Xue Yicheng Li	Department of Civil Engineering, Tongji University, Shanghai, China	薛亚东，同济大学土木工程学院教授
52	Deep learning based image recognition for crack and leakage defects of metro shield tunnel	Tunnelling and Underground Space Technology，2018	Hong-wei Huang Qing-tong Li Dong-ming Zhang	Key Laboratory of Geotechnical and Underground Engineering of Minister of Education and Department of Geotechnical Engineering, Tongji University, Shanghai, China	
53	Tunnel structural inspection and assessment using an autonomous robotic system	Automation in Construction, 2018	Elisabeth Menendez Juan G. Victores Roberto Montero	Robotics Lab Research Group within the Department of Systems Engineering and Automation at Universidad Carlos III de Madrid (UC3M),Spain	
54	Automated crack evaluation of a high-rise bridge pier using aring-type climbing robot	Computer-Aided Civil and Infrastructure Engineering. 2020	Keunyoung Jang Yun-Kyu An Byunghyun Kim2	Department of Architectural Engineering, Sejong University, Seoul, 05006, South Korea	
55	Drone scheduling for construction site surveillance	Computer-Aided Civil and Infrastructure Engineering, 2020	Wen Yi Monty Sutrisna	School of Built Environment, College of Sciences, Massey University, Auckland, New Zealand	

56	Real-time crack assessment using deep neural networks with wall climbing unmanned aerial system	Computer-Aided Civil and Infrastructure Engineering, 2020	Shang Jiang Jian Zhang	*the same as above*	
57	Noncontact Cable Force Measurement with Unmanned Aerial Vehicle and Computer Vision	Computer-Aided Civil and Infrastructure Engineering, 2020	Yongding Tian Cheng Zhang Jian Zhang	*the same as above*	
Few-shot learning					
58	Façade defects classification from imbalanced dataset using meta learning-based convolutional neural network	Computer-Aided Civil and Infrastructure Engineering, 2020	Jingjing Guo Qian Wang Yiting Li	Department of Building, School of Design and Environment, National University of Singapore, Singapore, Singapore	王骞，清华大学建设管理系本科，限位新加坡国立大学助理教授。在 BIM、三维扫描方面有较多成果。
59	Attribute-based structural damage identification by few-shot meta learning with inter-class knowledge transfer	Structural Health Monitoring, 2020	Yang Xu Yuequan. Bao, Hui. Li	*the same as above*	
The field of artificial intelligence					
60	Fully Convolutional Networks for Semantic Segmentation	CVPR,2015	Jonathan Long Evan Shelhamer	UC Berkeley, California, USA	

			Trevor Darrell		
61	Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks	NeurIPS,2015	Shaoqing Ren, Kaiming He, Ross Girshick, Jian Sun	Visual Computing Group Microsoft Research.	何恺明，广东省高考状元，清华大学本科，香港中文大学博士，现为 FAIR 研究科学家，深度学习明星学者，高被引科学家。首位获得 CVPR 最佳论文的中国人。
62	Deep Residual Learning for Image Recognition	CVPR,2016	Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun	Microsoft Research	
63	MaskR-CNN	ICCV,2017	Kaiming He Georgia Gkioxari Piotr Doll´ar	Facebook AI Research (FAIR)	
64	Densely Connected Convolutional Networks	CVPR,2017	Gao Huang	Cornell University	
			Zhuang Liu	Tsinghua University	
			Laurens van der Maaten	Facebook AI Research	
65	The One Hundred Layers Tiramisu: Fully Convolutional DenseNets for Semantic Segmentation	CVPRW.2017	Simon J´egou David Vazquez Adriana Romero Yoshua Bengio	Montreal Inst. for Learning Algorithms Montreal QC, Canada	
			Michal Drozdzal	Facebook AI Research (FAIR)	

66	Structured Knowledge Distillation for Dense Prediction	CVPR,2019	Yifan Liu Changyong Shu Jingdong Wang Chunhua Shen	The University of Adelaide, SA 5005, Australia.	
67	Nesti-Net: Normal Estimation for Unstructured 3D Point Clouds using Convolutional Neural Networks	CVPR,2019	Yizhak Ben-Shabat Michael Lindenbaum Anath Fischer	Mechanical Engineering Techion IIT Haifa, Israel	
68	PV-RCNN:Point-VoxelFeatureSetAbstractionfor3DObjectDetection	CVPR,2020	Shaoshuai Shi	CUHK-SenseTime Joint Laboratory, The Chinese University of Hong Kong	
			Chaoxu Guo Zhe Wang	SenseTime Research	
69	Grid-GCN for Fast and Scalable Point Cloud Learning	CVPR,2020	Qiangeng Xu Cho-Ying Wu Ulrich Neumann	University of Southern California, USA	
			Xudong Sun Panqu Wang	Tusimple, Inc	
70	RandLA-Net: Efficient Semantic Segmentation of Large-Scale Point Clouds	CVPR,2020	Qingyong Hu Bo Yang Linhai Xie Stefano Rosa Zhihua Wang	University of Oxford, UK	
			Yulan Guo	Sun Yat-sen University, 3National University of Defense Technology	

Appendix B. A list of Top journals in the field

Journal Title	IF 2019	分区 2020.01
Computer-Aided Civil and Infrastructure Engineering	8.552	JCR Q1 中科院 1 区
IEEE Transactions on Industrial Electronics	7.515	JCR Q1 中科院 1 区
IEEE Transactions on Intelligent Transportation Systems	6.319	JCR Q1 中科院 1 区
Automation in Construction	5.669	JCR Q1 中科院 1 区
Structural Health Monitoring-An International Journal	4.870	JCR Q1 中科院 2 区
Construction and Building Materials	4.419	JCR Q1 中科院 1 区
Structural Control and Health Monitoring	3.499	JCR Q1 中科院 2 区
Engineering Structures	3.548	JCR Q1 中科院 2 区

Author

He Zhili

Name: He Zhili,
Tel: 15151861213
E-mail: hzl@seu.edu.cn
Website: www.bimseu.com/hzl

Educational Background

- School of Civil Engineering, SEU, Master of Engineering 2019.09-
- School of Civil Engineering, SEU, Bachelor of Engineering 2015.09-2019.06