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Review on Machine Learning-based Defect Detection of Shield Tunnel Lining

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Abstract

At present, machine learning methods are widely used in various industries for their high adaptability, optimization function, and self-learning reserve function. Besides, the world-famous cities have almost built and formed subway networks that promote economic development. This paper presents the art states of Defect detection of Shield Tunnel lining based on Machine learning (DSTM). In addition, the processing method of image data from the shield tunnel is being explored to adapt to its complex environment. Comparison and analysis are used to show the performance of the algorithms in terms of the effects of data set establishment, algorithm selection, and detection devices. Based on the analysis results, Convolutional Neural Network methods show high recognition accuracy and better adaptability to the complexity of the environment in the shield tunnel compared to traditional machine learning methods. The Support Vector Machine algorithms show high recognition performance only for small data sets. To improve detection models and increase detection accuracy, measures such as optimizing features, fusing algorithms, creating a high-quality data set, increasing the sample size, and using devices with high detection accuracy can be recommended. Finally, we analyze the challenges in the field of coupling DSTM, meanwhile, the possible development direction of DSTM is prospected.

Keywords

shield tunnel, defect detection, machine learning, crack, water leakage

1 Introduction

As of January 2021, China's urban rail had reached 7,545 kilometers. Shield tunneling, which belongs to semi-concealed structures, is mainly used in the construction of underground sections of urban subways. As shield tunneling is the core facility of the subway lines, it is especially important to ensure the stability and safety of shield tunneling facilities. With increased operation time, much shield tunnel suffers cracks, water leakage, and other defects, which impact performance and operational safety. Various factors contribute to this situation, including changes in geological conditions, deterioration of lining material performance, construction defects, untimely or inadequate maintenance, etc. [1]. Currently, two main types of methods are used for defect detection in shield tunnel: manual inspection and manual coordination measuring instruments [2]. The former one is greatly influenced by subjective factors and requires a lot of labor. The latter is time-consuming and inefficient. Therefore, there is an urgent need to develop an objective, efficient, and highly accurate method to detect the surface of shield tunnel. Additionally, with the rapid growth of high-performance computers in recent years, machine learning is gradually being applied to the field of civil engineering. There have been significant advancements in crack detection, e.g., bridge cracks [3], roadway cracks [4], cracks in dams [5], etc. Therefore, it could be expected that the use of machine learning in the detection and extraction of defects in tunnel lining will make the procedure more objective, reliable, and efficient. Moreover, machine learning will provide an accurate record of defect morphology and parameters, which will revolutionize the inspection of underground tunnels to give it new vitality.

In the late 1980s, machine learning was initially employed in the field of civil engineering. Adeli and Paek [6] and others first proposed the use of machine learning in architectural building design. In terms of defect detection in shield tunnel lining, Sasama [7] developed automatic visual detection based on robots. It was a revolutionary change

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using artificial eyes from the traditional detection method. In China, Wang et al. [8–10] conducted a series of research on crack detection in tunnel lining and developed a comprehensive set of crack detection models and software algorithms. A simple interface for acquisition and crack identification effectively detecting small cracks with less noise was formed. Wang et al. [11] divided machine learning into traditional machine learning and deep learning according to the way of the feature set was established. Support Vector Machine, Artificial Neural Network, Decision Tree, K-nearest Neighbor, and Genetic Algorithm were all categorized as traditional machine learning, which required artificial construction of feature sets. Machine learning overcomes the subjectivity and inefficiency of traditional manual inspection, and enable more flexible, highly accurate and precise defect detection [2]. Several defect detection algorithms for shield tunnel lining have been developed, and they are frequently utilized to detect lining cracks, water leakage, and other minor problems. Furthermore, the structure and operation process of the algorithm model are different, which differ significantly in terms of detection accuracy and environmental adaptability accordingly. The detection effect of the algorithm model is also closely related to the quality of the data set, image data processing, and the choice of detection equipment. Thus, the major purpose of Defect detection of Shield Tunnel lining based on Machine learning (DSTM) is to select an appropriate algorithm model for the differing environmental features of the shield tunnel. Specifically, analyzing and summarizing the adaptive link between trained models and lining faults is critical.

This paper gives an overview of DSTM, with the goals of (1) presenting the main methods for establishing damage data sets in shield tunnel, (2) analyzing the application of different algorithms in tunnel defects, (3) comparing the benefits and drawbacks of DSTM, and (4) listing common devices used in tunnel lining defect detection. Finally, it discusses the problems of DSTM and offers advice on how to build and optimize DSTM.

2 Overview of DSTM

Shield tunnel lining involves many components, like expansion joints, structural joints, pipes, cables, etc. Besides, many factors that affect the unfavorable detection including irregular crack shapes, lacking of light, and uneven image brightness in the tunnel. They increase the challenge of defect detection compared to other structures such as roads, bridges, and dams. Fig. 1 shows the interference in

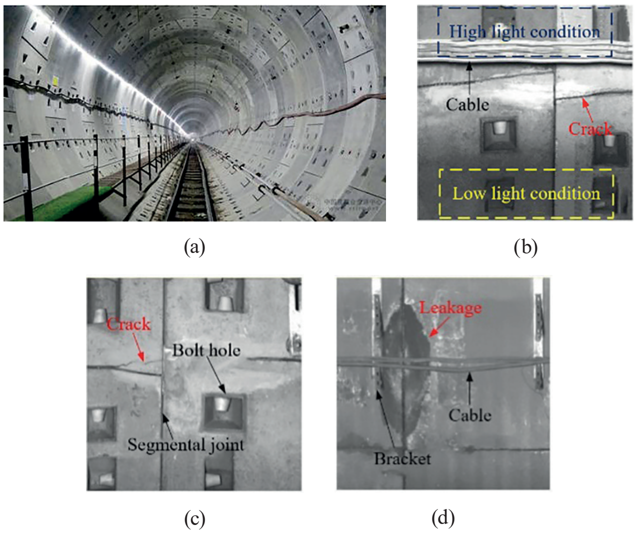


Fig. 1 Images of tunnel shield: (a) Lining surface, and (b)~(d) Several interferences on image recognition

target image recognition of shield tunnel. Machine learning can extract the image features that are unaffected or less affected by the above factors and can exert their advantages in the defect detection of shield tunnel lining. As the system of DSTM is shown in Fig. 2, the machine learning algorithms' model is conducted in computer language and trained using labeled training data from the shield tunnel's defect data set. Data set consists of a large amount of cracks, water leakage, and background interference feature information, such as segment joints, pipes, bolt holes, injection holes, etc. To achieve defect detection, the model continuously fits feature information using a machine learning algorithm. Then the trained model is used to process image data obtained from image acquisition devices in shielding tunnels. Various machine learning methods are used for data processing and tunnel defect detection, such as image classification (identifying the content of an image), target location (determining the image's content as well as its location), and semantic segmentation (labeling each pixel in the image) of cracks, water leakage, etc.

2.1 Algorithm overview of machine learning

The automatic detection algorithms of concrete crack images can be divided into two categories: digital image processing and machine learning. Digital image processing needs to manually design a unique rule in single image feature detection. It leads to poor adaptability of the algorithms and makes it challenging to apply in shield tunnel with complex background noise and changing lighting conditions. To tackle the generalization problem, many researchers have utilized machine learning methods to the

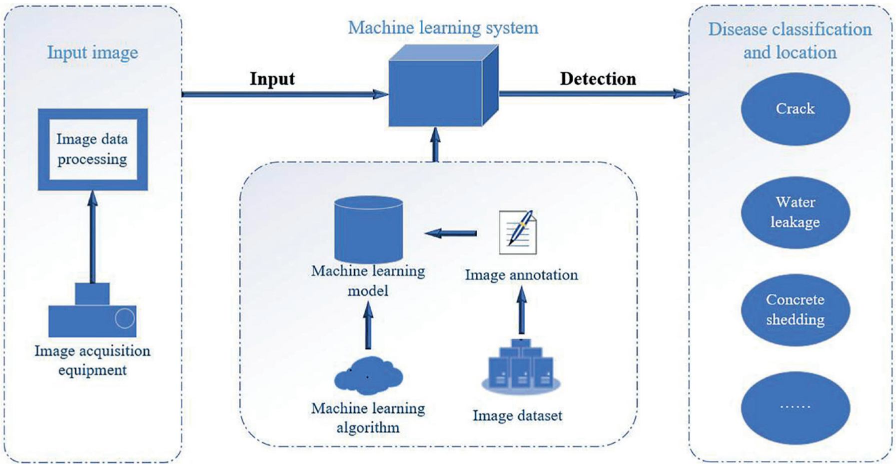


Fig. 2 Defect detection system in Lining

detection of cracks in shield tunnel, water leakage, and other defects by learning multidimensional features in the image sample data.

Convolutional Neural Network (CNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree (DT), K-nearest Neighbor (KNN), and Genetic Algorithm (GA) are commonly used for defect detection in shield tunnel lining. Among them, CNN is the most widely used algorithm for defect detection of shield tunnel lining, which has the property of automatically learning features from data [12]. CNN provides significant advantages in terms of algorithm running time when compared to traditional image recognition algorithms [13]. Besides, compared with ANN, SVM, DT, and KNN algorithms, CNN is superior to the other four algorithms in terms of image recognition accuracy and miss rate, as shown in Fig. 3 [14, 15]. Accuracy refers to the ability of the model to judge the overall sample correctly, and higher values indicate better performance. The miss rate reflects the model's ability to correctly predict negative samples, and smaller values represent better performance.

In addition, ANN, SVM, DT, KNN, and GA require researchers to manually design several complex features to extract defects. Among them, KNN and DT are relatively intuitive. The former one is nonparametric strategies that uses similarity measurement to identify instances more similar to specific data. The latter is tree structures in which each node studies the value of a specific feature. ANN and the SVM are more complex method. ANN is a general-function approximator made up of multi-layer interconnected nodes and neurons with several optimal solutions. SVM can efficiently perform nonlinear classification and implicitly map the input to a high-dimensional feature space in which the different classes are linearly separable. GA applies a large number of filters to the previously manually processed data set and uses the algorithm to select the best combination of filters. The purpose is to achieve the best detection results [16].

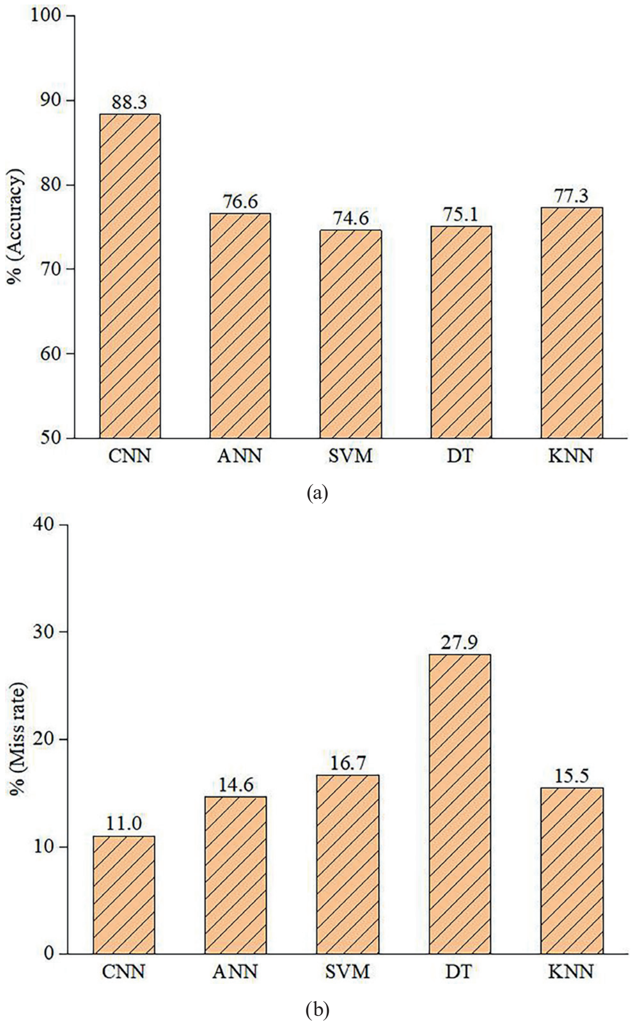


Fig. 3 Comparison of five kinds of algorithms: (a) Comparison of accuracy, and (b) Comparison of miss rate

2.2 Performance evaluation of DSTM

The advantages and disadvantages of the DSTM are measured based on the fitting effect between the test results of image data and the real defect results by the classifier. Due to the complex background disturbance information of the shield tunnel, many factors must be considered in performance evaluation. Table 1 lists various performance indices and their corresponding calculation formulas used to evaluate the performance of DSTM. These performance indicators are mainly used to evaluate the detection effect of the DSTM and can also be used to compare the differences in the detection quality of different models. It is not enough to evaluate a model only by a certain performance index, which lacks scientificity and comprehensiveness. Therefore, when comparing the recognition performance of multiple models, the joint use of multiple evaluation methods can more objectively describe the detection effectiveness of the model.

3 Method of DSTM

First, the method of DSTM requires to establish an image data set and select a suitable algorithm, and then using the sample data to train the prediction model. By learning the characteristics of the defect marked in the sample data, it can realize the defect detection in a specific scene. Currently, there are many studies on road and bridge detection using machine learning algorithms, but there aren't many studies on defect detection in subway tunnel. Besides, there are many studies on crack detection but not many on water leakage and concrete shedding detection.

Table 1 Performance evaluation of DSTM [14]

performance index	Formula
Sensitivity (TPR)	TPR = TP/P
Specificity (SPC)	SPC = TN/N
Precision (PPV)	PPV = TP/(TP + FP)
Negative predictive value (NPV)	NPV = TN/(TN + FN)
False positive rate (FPR)	FPR = FP/N
False discovery rate (FDR)	FDR = 1-PPV
Miss Rate (FNR)	FNR = FN/P
Accuracy (ACC)	ACC = (TP +TN)/(P + N)
F1 score (F1)	F1 = 2TP/(2TP + FP + FN)

Where: P is the defect sample, that is, the positive sample; N is the defect free sample, i.e., negative sample; TN is called true negative rate, which denotes that the actual number of negative samples equals the number of samples projected to be negative; FP is false positive rate, which indicates that the actual number of negative samples is predicted to be positive samples; FN is false negative rate, which indicates the number of samples predicted to be negative from positive samples; TP is true positive rate, which indicates the number of samples predicted to be positive samples.

To fully understand the development of DSTM, the following section collects and analyses the machine learning methods used in previous literature and attempts to discuss the indicative function of monitoring defect development for structural health and decay.

3.1 Data set establishment

Currently, data, computing power, and algorithms are major influence elements in the development of artificial intelligence, which complement and reinforce each other. Among them, data is the foundation, and any research cannot be separated from it. There are usually two solutions to the source of the data set: one is to find out a publicly shared data set on the Internet, and the other is to create a new data set personally. The method of creating a new data set is usually chosen in most studies due to the lack of a publicly shared data set. Therefore, the impact of a data set on defect detection performance is discussed in terms of creation method, sample size, and universality.

The way for creating the data set has a significant impact on subsequent detection accuracy. In addition, ensuring clarity and contrast of crack features can improve the accuracy of the algorithm results. When establishing the data set, labeling the data set is an important step which is usually done manually. Besides, labeling is extremely time-consuming and can easily cause wasted efforts and labeling errors when processing a large amount of image data. This problem affects the accuracy of defect detection in shield tunnel [17, 18]. Therefore, researchers have proposed transfer learning [19, 20] and active learning [21] to reduce the labeling time and workload. Currently, there aren't many studies on DSTM, so it is difficult to obtain the relevant imaging data. Transfer learning can be used to label sparse data (target domain) by using auxiliary domain data (source domain) to train a model. Fig. 4 shows an intuitive example about transfer learning. It can not only solve the problem of difficult to obtain labeled data in the tunnel but also save the cost of manual labeling. Transfer learning can improve the precision of the classification model [22], which uses a small number of pre-labeled samples to train the model. However, its performance is not preferable compared with the whole-process manual labeling. Additionally, active learning uses both labeled and unlabeled samples to establish models, which selects high-quality and important samples through a sample selection strategy. Then asks human experts to accurately label images. Though this process can't still do without manual involvement, the labor time and workload

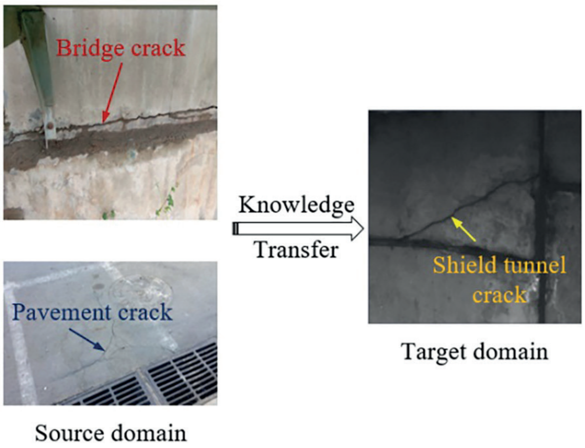


Fig. 4 Intuitive example about transfer learning

have been significantly reduced compared to the traditional method of manual labeling. What's more, the introduction of incorrect labels can be avoided by asking human experts to label the selected samples [23]. Active learning could be expected to achieve the performance of training with full-sample manual labeling eventually by iteratively querying unlabeled samples and asking human experts to label images. The general process is shown in Fig. 5.

The sample size has the same effect on the detection performance of the model in addition to the influence of the method used to create the data set. As for crack detection, the vast majority of research's sample size exceed 2,000, and some even reach 200,000. There are many sample features because of the influence of complex background information like light, interference, and segmental connections in the shield tunnel. To increase the size of the training sample data set and avoid the occurrence of over-fitting, the researchers have enhanced the diversity of data by utilizing random rotation, horizontal flip, translation, reflection, random clipping, and contrast adjustment [24–27]. As seen in Fig. 6, single and insufficient sample of training data set will lead to over-fitting. Therefore, it is suggested that the scale of the data set used for model training should be large. Only when there are enough samples can a model with better performance be trained.

Additionally, the data set's universality also affects the detection performance of the algorithm. The lack of high-quality data sets with complete annotations [28, 29] is one of the major obstacles when developing new algorithms. In most studies, researchers rely on their own data sets to test proposed methods, and the number of publicly shared data sets designed specifically for evaluating crack defect are very restricted. When creating the data set, researchers pay particular attention to the features of their algorithms while ignoring other features unrelated to their experiments. Therefore, it is not objective to rely on self-established data set to evaluate the performance of different algorithm models.

3.2 Algorithm selection

3.2.1 Crack detection

Crack is one of the most common defects in tunnel structures and also the most important control projects in any phase of tunnel's operation and maintenance. Therefore, the maximum allowable width of the crack is specified for security. The allowable width of the segment crack in shield tunnel is 0.2 mm, and it is 0.3 mm for other structures [30]. During patrol inspection, it is often impossible to notice such subtle defects, and crack width cannot be measured. Additionally, the image information of the crack defect on the shield tunnel lining surface mainly has the following three characteristics [31]: 1) the shape of the defect area is complex because the crack on the lining surface is generated spontaneously under a variety of actions. They are not regular lines, circles, and other simple geometric shapes. 2) the randomness of defect distribution is strong, and crack

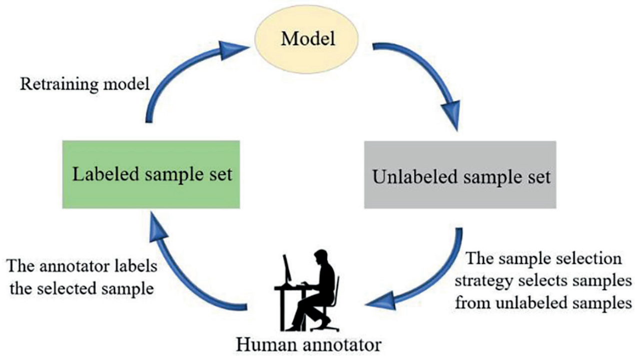


Fig. 5 General process of active learning algorithm

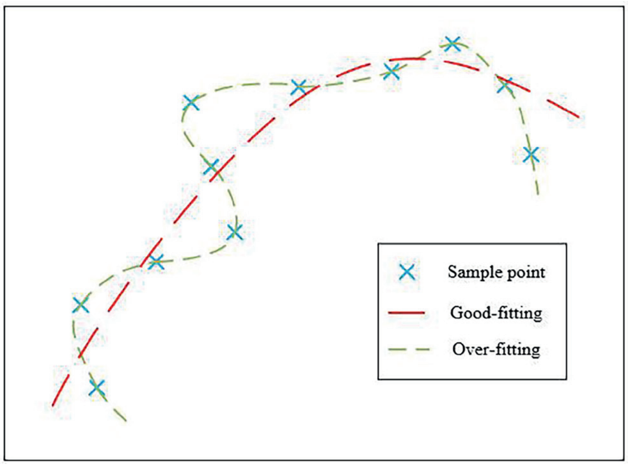


Fig. 6 Over-fitting status

defects may occur in any area of the segment. Therefore, it is difficult to accurately predict the specific location of the crack in the spatial coordinate system. 3) the connectivity of the defect area is poor, and the size of the crack defect is usually small. There are usually several independent crack defects at the same time, which are not connected. The reasons of above phenomena are the lack of accurate detection equipment and sufficient detection time.

Before the machine learning algorithm was introduced into crack detection in the lining, the automatic detection algorithm was based on the image processing method, which used the created unique rules manually for individual image features to realize defect detection. However, as the complexity of the detection environment increased, the method's adaptability was low, which made it difficult to meet the accuracy demand in actual detection. Therefore, researchers applied the machine learning method into crack detection for its excellent generalization ability and robustness. It can detect the crack information in the image by learning the multidimensional features in the image sample data so that the problem of environmental adaptability could be solved. Additionally, detection methods based on traditional machine learning need to design manually multiple complex features of crack to be extracted. Then the crack detection was completed using Artificial Neural Network, Support Vector Machine, or Decision Tree.

Artificial Neural Network (ANN) technology has played a major role in the development of crack image recognition. Besides, BP neural network has been widely used in crack image detection as a typical ANN algorithm. The BP neural network can be used to train the model for its learning ability and fault tolerance [32, 33], and separate the crack pixels from the background by selecting a suitable threshold value [34]. The accuracy of conventional BP neural networks in crack detection is generally not high due to the choice of initial weight and threshold. Therefore, some researchers [35, 36] have proposed utilizing the genetic algorithm and the artificial bee colony algorithm to optimize the BP neural network so that the accuracy of BP neural network is greatly improved. However, the problems of poor global searching ability, slow convergence, and easily falling into a local minimum have not been overcome.

Both BP neural network and Support Vector Machine (SVM) have been widely concerned. Some researchers [37–39] have compared the accuracy of the two and concluded that the crack detection algorithm based on SVM has higher detection accuracy. The reason is that it has globally optimal nonlinear classification ability, good generalization performance, and nonlinear classification ability based on the kernel function. Therefore, SVM has strong advantages in solving some classification problems, e.g., small sample size, nonlinearity, and high-dimensional space [40]. To overcome the environmental influence of crack detection accuracy, researchers improved the SVM algorithm. One way was to create a Gaussian scale-space by convolution operation to remove illumination interference for extracting the crack image feature vector [41]. The other is by detecting cracks in concrete surfaces based on high-dimensional feature compression of the image [42]. Finally, the detection accuracy of both is more than 90% for the crack defect.

Although Decision Tree's detection accuracy is lower than the neural network when used for concrete crack detection, it has a feature selection capability of extracting the concrete crack's features. The most commonly used DT algorithms are ID3 and C4.5 [43]. ID3 algorithm is simple in structure, and the crack detection results are perfect. But this method is only suitable for a small amount of data, and it is not robust to noise [40]. To tackle the data volume problem existing in the ID3 algorithm in the process of crack detection and classification, some researchers [44] proposed the C4.5 algorithm. They replaced the core information gain of the ID3 algorithm with the information gain ratio so that it had a good detection effect for large data volumes.

In summary, various crack image features and combinations are used in research when using traditional machine learning methods to detect the crack in the shield tunnel. However, the complexity of crack features leads to serious deviation between the extracted features and the actual situation. In addition, the process of feature extraction relies on the designers' prior knowledge and experience in parameter fitting making the detection accuracy difficult to meet the application requirements [12]. Therefore, researchers have proposed Convolutional Neural Network (CNN) for automatic crack detection. With the support of a large amount of data, CNN can complete automatically feature extraction without designing artificially different feature extractors for different targets. It greatly improves the automatic detection's accuracy [45]. Besides, CNN has obvious advantages in the interference from complex background information, e.g., segment connections, cables, pipes, and LED lights in shielding tunnels. CNN consists of an input layer, an output layer, and several hidden layers, as shown in Fig. 7. There is no connection between neurons in the same layer and neurons in different layers are fully forward connected. In a study, CNN was used to compare the performance with SVM and DT in detecting actual cracks, and the accuracy and F1 score of CNN were better than 10% [17]. According to a combinatory deep learning heuristic post-processing scheme, the steps of the algorithm that detects and pinpoint the crack position are shown in Fig. 8. Some CNN evolution algorithms have been optimized in terms of network structure, algorithm fusion, and generalization ability, which makes the model have conspicuous advantages in crack defect detection. Table 2 [24, 46–52] summarizes the evolutionary algorithms and application examples of the corresponding CNN.

The CNN-based evolutionary algorithm optimizes the detection model to some extent from various aspects, e.g., training efficiency, algorithm fusion, and detection accuracy, as shown in Table 2. Although the accuracy of FCN is lower than the existing advanced crack detection algorithms such as Segnet, its training time has been greatly reduced. FCN is an end-to-end model, which does not require post-processing or pre-processing for crack detection [53–55].

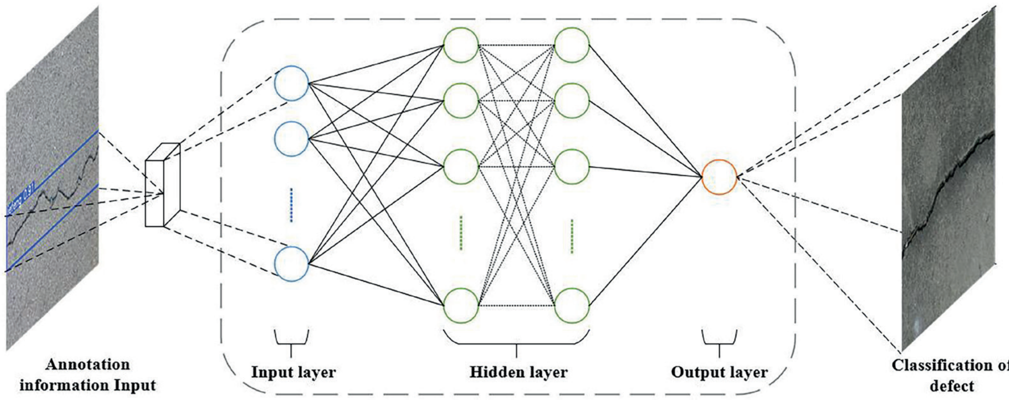


Fig. 7 CNN structure with two hidden layers

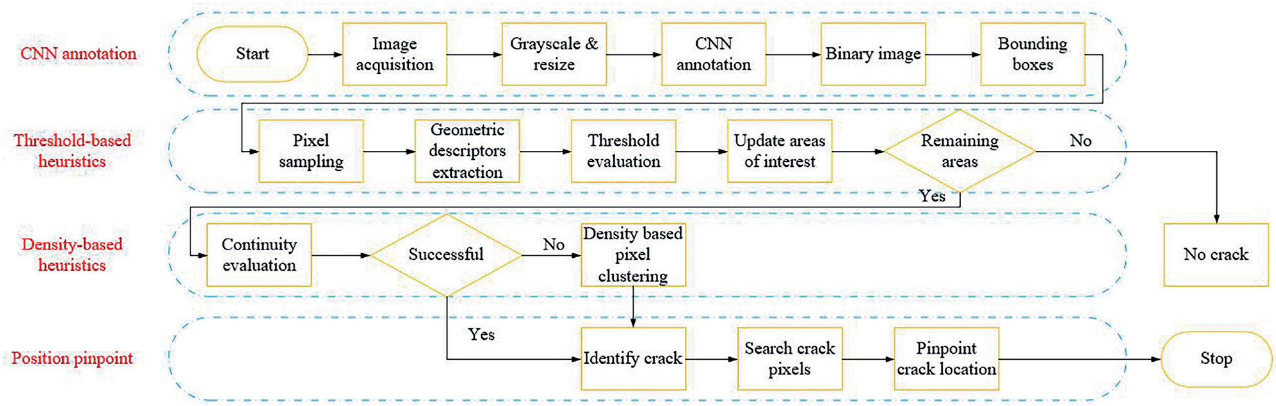


Fig. 8 Methodology flowchart of the combinatory deep learning heuristic post-processing

Table 2 CNN evolutionary algorithms and application examples

Research objects	Model of choice	Sample size	Detection accuracy	Researchers and time
Crack	GoogLeNet Convolutional Neural Network	7560	ACC = 95.24%	Xue and Li, 2018 [46]
Crack and leakage	Fully Convolutional Network (FCN)	299170	ACC = 99.20%	Huang et al., 2018 [47]
Crack	Dense connected Convolutional Network (DenseNet)	10800	ACC = 95.83%	Gao et al., 2020 [48]
Crack	AlexNet Convolutional Neural Network	2073	ACC = 96.64%	Kim and Cho, 2018 [49]
Crack	SegNet with focal loss function (FL-SegNet)	10000	ACC = 99.52%	Dong et al., 2019 [24]
Crack	Deep Convolution Neural Network (DCNN)	3420	ACC = 98%	Dorafshan et al., 2018 [50]
Crack and leakage	Faster R-CNN target detection algorithm	4139	ACC = 80.91%	Xue et al., 2020 [51]
Crack	Cascade R-CNN target detection algorithm	9661	ACC = 96%	Gong, 2020 [52]

By fine-tuning the CNN model, Alexnet reduces the training time. It starts training on a pre-trained model rather than a randomly initialized model to minimize the training process and improve the training efficiency of the algorithm [56]. Segnet, a new end-to-end model based on FCN, consists of convolutional feature extraction, convolutional acceptance domain expansion, multi-scale maximum pooling, and jump connection of the feature fusion module. It is superior to other algorithms in terms of accuracy [57]. Fast R-CNN is based on regional proposal network (RPN) and uses a candidate box instead of the original selective search algorithm [58, 59]. It has been improved based on R-CNN making the speed and accuracy of target detection and recognition higher. However, the proper end-to-end detection is not realized because the process of faster R-CNN target detection includes target identification and target detection, and the amount of computation is still large. Therefore, the real-time effect cannot be realized [60, 61]. Utilizing the optimized Cascade R-CNN can effectively improve the accuracy and efficiency of identification. Cascade R-CNN model achieves the goal of optimizing continuously the prediction results by cascading multiple detection networks [62, 63]. In addition, researchers compared the architecture of Faster R-CNN and Cascade R-CNN, shown in Fig. 9. In brief, various evolutionary models based on CNN go through an algorithm improvement's process to improve the training speed, environmental adaptability, and recognition potential of the model.

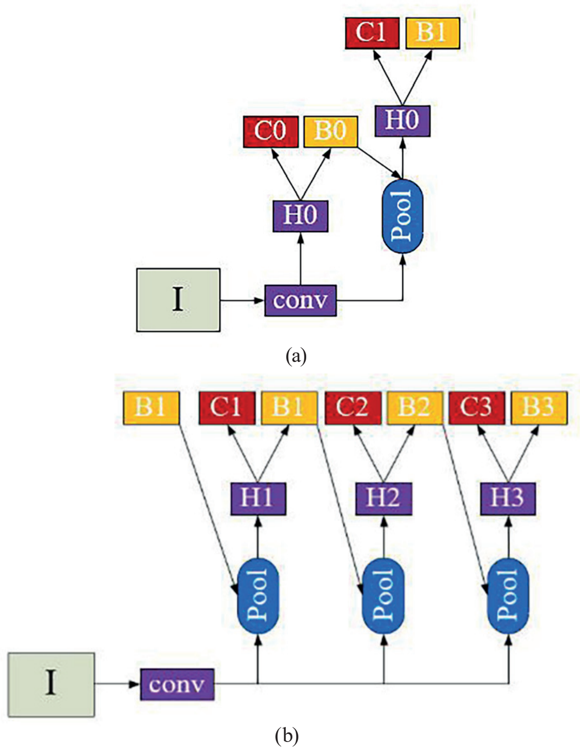


Fig. 9 The architectures of different frameworks [62]. "I" is input image, "conv" is backbone convolutions, "Pool" is region-wise feature extraction, "H" is network head, "B" is bounding box, and "C" is classification; (a) Faster R-CNN, (b) Cascade R-CNN

3.2.2 Water leakage detection

Based on the selection of construction technology and lining structure, there are a large number of circumferential joints, longitudinal joints, bolt holes, and injection holes in the shield tunnel, which are potential leakage channels in shield tunnel. Water leakage, the main defect of underground shield tunnel and accounting for more than 60% [64–66], which is the most important and difficult detection content in DSTM. Compared with crack detection, there aren't many relatively studies on water leakage defect, and the algorithm model used is similar to the crack detection algorithm model. The difference is that the focus of the quantization parameters of the two is different. Researchers often use the length, width, and shape of cracks to assess the severity of the defect, while water leakage is more concerned with area and type (e.g., wet trace, seepage, drip, and seepage sludge). In this section, the research content of water leakage defect is presented from two aspects: the characteristics of the water leakage image of the shield tunnel and the algorithm to detect water leakage.

As for the characteristics of the water leakage image, the shape of the water leakage defect is random and the differences within the category are largely due to the influence of joint, interference shielding, background noise, and changing illumination. To eliminate the above effects, some researchers [13, 67] divided the water leakage pattern into six categories: joint + bolt hole, joint + bolt hole + pipeline, joint + bolt hole + pipeline + support, joint + bolt hole + shadow, joint + bolt hole + pipeline shielding + shadow, and the area of water leakage is not connected. As shown in Fig. 10. This method is suitable for water leakage detection of various disturbance factors and has great advantages.

In terms of selecting the detection algorithm for water leakage, the traditional machine learning method cannot adapt to the complex image characteristics of water leakage. Additionally, CNN is widely used and has better performance in water leakage detection because of its strong adaptability and high accuracy in complex environments. Table 3 [13, 67–69] lists the relevant research results based on machine learning methods for water leakage detection. In crack detection, some algorithms have the same functions as in water leakage detection, so they are not repeated here.

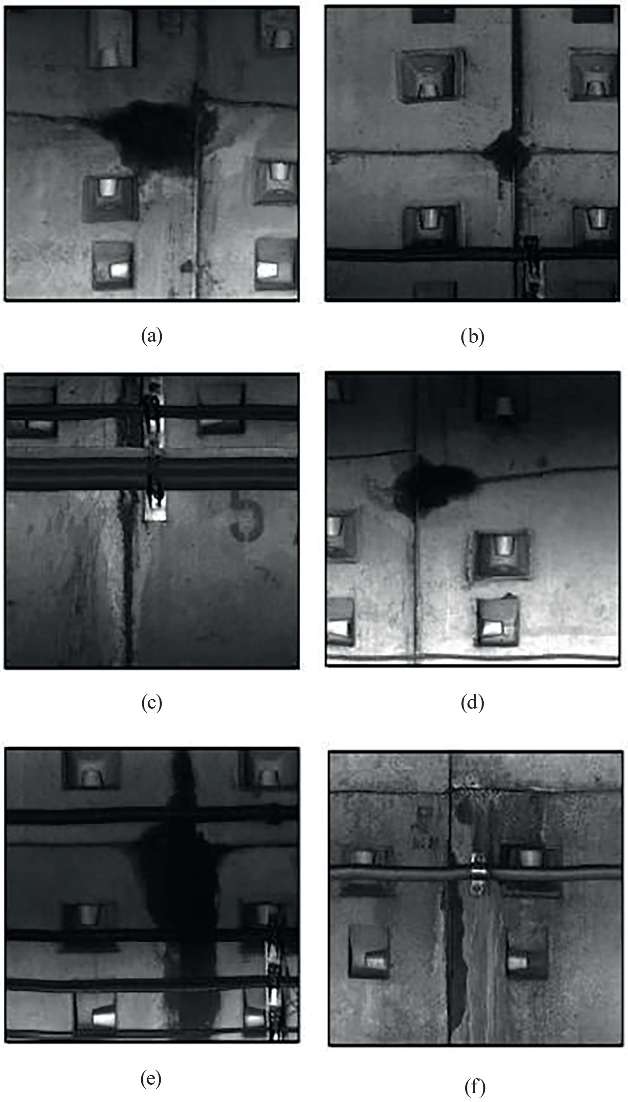


Fig. 10 Image categories of water leakage in shield tunnel [13, 67]: (a) joint + bolt hole; (b) joint + bolt hole + pipeline; (c) joint + bolt hole + pipeline + support; (d) joint + bolt hole + shadow; (e) joint + bolt hole + pipeline shielding + shadow; (f) the area of water leakage is not connected

3.2.3 Defect evolution monitoring

As discussed in the previous sections, most researchers are aimed at the length, width of cracks and water leakage area in shield tunnel lining to evaluate the defect grade of lining, which have some limitations. It is worth noting that the rate of defect development also has some influence on defect evaluation. Besides, some researchers [70] have proposed that the structural condition and deterioration of the tunnel can be determined by detecting the development process of the defect.

Jenkins et al. [71] proposed a system to detect the development of tunnel lining. They used a series of overlapping cameras placed on a tram to detect the change by comparing the image of the previous scan as a template with the best matching image of the current scan. After matching the images, the normalized filter was applied to detect the difference between the two images. Tinspect, a tunnel lining evolution monitoring system proposed by Attard et al. [72], which relied on the low-cost camera equipment mounted on the monorail for train inspection to obtain image data. Then comparing and analyzing image data to determine the difference between the front and rear images. The detection accuracy of this system was high, but a camera can only monitor a limited area of the tunnel. Therefore, they improved it by using a CNN architecture to realize defect detection. If you accept a slightly higher false positive rate, this method is superior to other existing methods [70].

At present, most inspection studies are concerned with cracks and water leakage, rather than defect evolution. Sometimes it is more useful to study the evolution of this deformation, which can better reflect the condition of the tunnel structure and its deterioration. Deformation of tunnel segments leads to visible change in the lining, which is an important prerequisite for the prevention of structural damage in early detection. Additionally, the threshold value of defect development has not been determined, so it can only be used as a reference. Some research has been carried out to reveal the objective relationship between the defect development and the degree of damage in the structure, which provides an idea and basis for further research.

3.3 Image acquisition equipment

Fast, efficient, and accurate defect detection in tunnels requires excellent algorithms, high-quality data sets and the appropriate equipment. The combination of them can improve detection procedure. It can achieve comprehensive intelligent detection by integrating various defect detection technologies into patrol inspection equipment.

Table 3 Application example of water leakage defect detection

Research objects	Model of choice	Sample size	Detection accuracy	Researchers and time
Water leakage	Fully Convolutional Network (FCN)	10000	ACC = 77.74%	Xiong et al., 2020 [67]
Water leakage	Fully Convolutional Network (FCN)	12000	ACC = 99.10%	Huang, 2017 [13]
Water leakage	FCN-RCNN	552	ACC = 98.10%	Gao et al., 2019 [68]
Water leakage and Concrete spalling	Mask R-CNN	9680	ACC = 88.76%	Xu et al., 2020 [69]

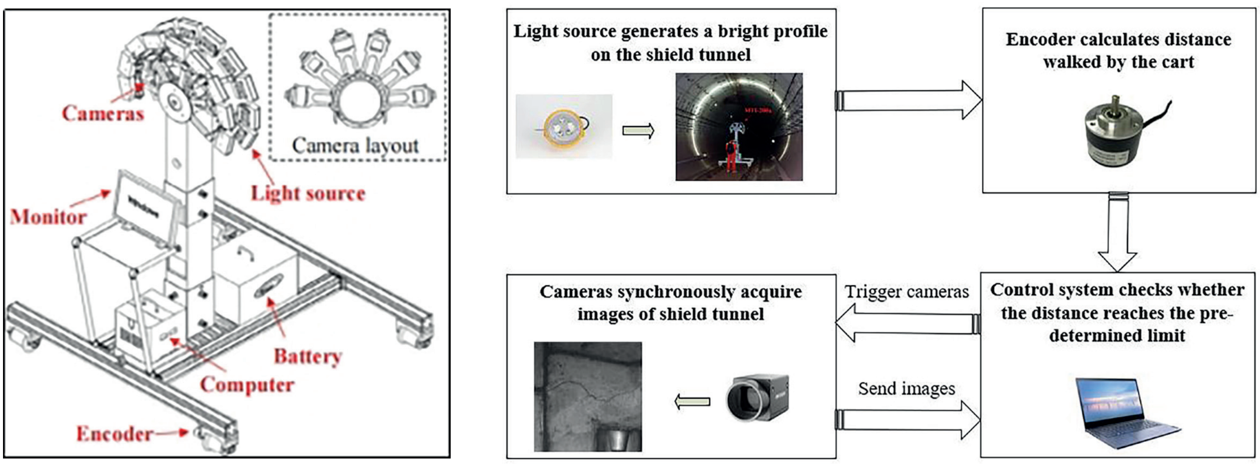
The selection of equipment has a certain impact on the detection performance of the model. The selected equipment must collect all-around and high-resolution image data in the tunnel and meet the requirements for fast image data acquisition to achieve optimal detection performance. Currently, many countries or organizations have developed advanced detection equipment, as shown in Table 4 [74–81]. The sketch map and schematic of acquisition procedure of images acquisition system are shown in Fig. 11. For the high-resolution requirements of DSTM, most of researchers use industrial line-scan cameras to realize the goal of image acquisition. It essentially satisfies the image definition requirements of the detection model. Additionally, it should be noted that there are certain speed requirements for the detection equipment in the crack detection of the tunnel to ensure normal operation for image acquisition. At present, the speed of commercial detection models in various countries is generally 5–20 km/h [73], which does not yet meet the requirement on the scene of real-time detection.

Currently, many studies on tunnel detection equipment are still in the development and experimental stages, and there are imperfections in equipment technology and processing methods. For example, if the acquisition speed of the detection model based on an industrial line scan camera is too fast, the captured image can be easily lost or distorted. Besides, when capturing tunnel images from a long distance, image processing, fusion, and defect quantification take a long time. So, it is difficult to ensure the accuracy and efficiency of analysis at the same time. Therefore, to take full advantage of the high precision and high efficiency of machine learning in practical applications, further improvement of research on image acquisition equipment is needed.

Table 4 Defect detection equipment of tunnel

Research objects	Visual system composition	resolving power	Image acquisition speed	Research organization and time
Cracks and water leakage	Linear array industrial camera	0.3 mm per pixel	5 km/h	Tongji University, 2017 [74]
Cracks, concrete spalling and water leakage	Area array industrial camera	0.3 mm per pixel	30 km/h	Nanning rail transit Group Co., Ltd., 2020 [75]
Segment deformation	Industrial camera	0.3 mm per pixel	5 km/h	Tongji University, 2015 [76]
Crack	Linear array industrial camera	0.3 mm per pixel	2.5 km/h	A Swiss group, 2016 [77]
Crack	Point Grey industrial camera	1 mm per pixel	8 km/h	Carlos III University, Madrid, Spain, 2018 [78]
Cracks, concrete spalling and water leakage	Area array industrial camera	0.3 mm per pixel	30~40 km/h	Central South University, 2018 [79]
Crack	Linear array industrial camera	0.5 mm per pixel	100 km/h	Shandong University of science and technology, 2021 [80]
Cracks, falling blocks and water leakage	Linear array industrial camera	0.2 mm per pixel	6 km/h	Tongji University, 2017 [81]

Where: "image acquisition speed" denotes the control system calculates the distance walked by the detection device through the encoder and triggers the cameras after reaching the pre-determined limit. Therefore, the image acquisition speed is equal to the speed of the cart. The image needs to be acquired in a stable and clear manner, so a robust lighting system and the vibration of the camera decide the running speed of the equipment.



(a) (b)

Fig. 11 Images acquisition system used in Huang et al. [74] (a) Sketch map of the equipment, and (b) Schematic of acquisition procedure

4 Challenges in DSTM

At present, the research and application of machine learning represented by deep learning have gotten some achievements in the field of defect detection in tunnel lining. It has effectively improved the technical level of subway operation, which promoted the cross-domain penetration of railway engineering in China. However, it should also be recognized that the research on deep learning is still in an immature stage, and most of the results are obtained through experiments or empirical methods. Theoretical research should be more in-depth, and its application in practical engineering also faces great challenges. An overall analysis of previous literature has shown that the existing models for defect detection generally have the following problems:

(1) Problems of quantitatively analyzing the damage degree caused by cracks, water leakage, and other defects in the tunnel structure still exist. The geometric size (including length, width, and depth), shape (e.g., transverse crack, longitudinal crack, block crack, and mesh crack), cause (loaded crack and unloaded crack), and location of the crack all affect the evaluation of the risk degree of the shield tunnel structure. However, most of the research still focus on the geometric size and shape of cracks, which have some limitations in assessing the degree of crack damage in structures.

(2) Currently, there is a large gap between the technical system and the corresponding guidelines for tunnel defect assessment in China. The existing technical standards for tunnel maintenance and inspection mainly refer to bridges and the inspection objects in the existing standards are mainly for mountain tunnels. It is a pity that there aren't many standards for urban shield tunnel. The research detached from the standard specifications is unrealistic, and its practical significance is not enough.

(3) The speed of image acquisition of the detection system cannot meet the requirements. In addition to the requirement for detection accuracy, there is also a certain speed requirement for image acquisition so as not to affect the safety of train operation and normal operation. At present, the detection model based on machine learning is unable to achieve high precision and efficiency when applied to practical projects, so it is rarely used in subway operation practice.

(4) The universality of the data set is not high. There is no publicly shared data set on defect detection of shield tunnel lining. Most researchers create data sets according to the characteristics they are interested in and then compare the accuracy of different models in their own data sets. Therefore, the experimental results are difficult to convince.

5 Conclusions

This paper presented an overview of DSTM and focuses on machine learning techniques for crack and water leakage detection. It summarized the machine learning models' performance evaluation of differing shield tunnel deterioration indices. The impacts of method selection, data set creation, and detecting equipment on the machine learning model's detection performance were also explored. The following conclusions can be drawn:

(1) In small data sets, CNN is prone to over-fitting resulting in a decline in detection accuracy, but SVM has global optimal nonlinear classification ability and good generalization performance. Therefore, SVM can be preferred applied in the small data sets.

(2) Compared with traditional machine learning methods, CNN have obvious advantages in detection accuracy. CNN can automatically complete feature extraction without designing different feature extractors for differing targets.

(3) The size and universality of the data set have a significant impact on the accuracy of the DSTM method. A small sample size will lead to poor adaptability of the model in the complex environment of the shield tunnel. The diversity of data can be enhanced by random rotation, horizontal turnover, translation, reflection, random clipping, adjusting contrast, and other methods to improve the detection accuracy.

(4) To achieve the best detection performance of the detection model, matching equipment and instruments are also needed. The selected equipment is required to collect all-around high-definition image data in the shield tunnel and meet the requirements for rapid image data collection.

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