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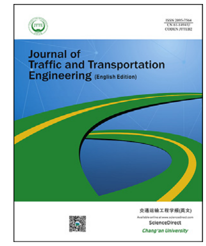

Review Article

Research and applications of artificial neural network in pavement engineering: A state-of-the-art review

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HIGHLIGHTS

- Frontiers of artificial neural network (ANN) in pavement design, construction, inspection and maintenance were reviewed.
- Three mainstream ANN architectures for different application scenarios were summarized.
- Five research challenges and prospects of ANN application in pavement engineering were analyzed.
- Standardized literature search and classification methods were implemented.

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ABSTRACT

Given the great advancements in soft computing and data science, artificial neural network (ANN) has been explored and applied to handle complicated problems in the field of pavement engineering. This study conducted a state-of-the-art review for surveying the recent progress of ANN application at different stages of pavement engineering, including pavement design, construction, inspection and monitoring, and maintenance. This study focused on the papers published over the last three decades, especially the studies conducted since 2013. Through literature retrieval, a total of 683 papers in this field were identified, among which 143 papers were selected for an in-depth review. The ANN architectures used in these studies mainly included multi-layer perceptron neural network (MLPNN), convolutional neural network (CNN) and recurrent neural network (RNN) for processing one-dimensional data, two-dimensional data and time-series data. CNN-based pavement health inspection and monitoring attracted the largest research interest due to its potential to replace human labor. While ANN has been proved to be an effective tool for pavement material design, cost analysis, defect detection and maintenance planning, it is facing huge challenges in terms of data collection, parameter optimization, model transferability and low-cost data annotation. More attention should be paid to bring

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multidisciplinary techniques into pavement engineering to tackle existing challenges and widen future opportunities.

1. Introduction

Artificial neural network (ANN), particularly deep neural network (DNN), is one of the fastest-growing artificial intelligence (AI) techniques, leading the development of most industries (Moayedi et al., 2020; Schmidhuber, 2015; Zhang et al., 1998). Driven by the neural network and big data, pavement engineering is facing more opportunities as well as various challenges. Given that a substantial amount of complicated problems exist in pavement engineering applications, it is imperative to find an effective tool to replace huge complicated calculations in traditional methods. On the other hand, researchers hope to discover more valuable or interesting knowledge behind the physical phenomenon and experimental data. ANN, as a most promising data-driven technique, is of great concern and has been proved to have a degree of success and reliability in numerous academic subjects and projects (Hou et al., 2020; Khan and Yairi, 2018; Srikanth and Arockiasamy, 2020; Zhu et al., 2017).

Early in the 1990s, different subjects in the field of pavement engineering have been studied using ANNs. Haussmann et al. (1997), and Ceylan et al. (1998, 1999) developed ANN models as alternative analysis design tools to reduce the complexity of finite-element analysis programs, efficiently predicting pavement stress under different structure design schemes. Attoh-Okine and Fekpe (1996), Najjar and Basheer (1997) and Zaman and Zhu (1998) utilized ANNs to estimate the mechanical property and durability of pavement materials. In addition to pioneering exploration in pavement structure and material design, the feasibility of ANNs for pavement distress recognition and maintenance planning has been proved in earlier research (Fwa and Chan, 1993; Kaseko and Ritchie, 1993). In recent years, some studies made efforts to employ ANNs at different stages of pavement engineering, including pavement design (Ghorbani et al., 2020; Naderpour et al., 2018), construction (Androjić and Dolaček-Alduk, 2018; Roxas et al., 2019), inspection and monitoring (Tong et al., 2018; Zhang et al., 2017), and maintenance (Elbagalati et al., 2018; Hafez et al., 2019). Previous findings on the ANN application in pavement engineering suggest its huge potential for further development.

1.1. Classification of artificial neural network

Inspired by the human nervous system, Rosenblatt (1958) created the perceptron, which is the basis of the early ANNs. The perceptron based ANNs generally consists of several layers of nodes. In the ensuing decades, recurrent neural network (RNN) and convolutional neural network (CNN), also known as deep neural network (DNN) or deep learning, were proposed to extend the application scope (Schmidhuber, 2015). Another key impetus for ANN development is the great advancements in training techniques and computer hardware such as back propagation (BP) algorithm and graphics processing unit (GPU) computing. According to network architecture, ANNs can be classified into the following three major types (Fig. 1).

- Multi-layer perceptron neural network (MLPNN).
- Recurrent neural network (RNN).
- Convolutional neural network (CNN).

MLPNN is a typical ANN using feed forward architecture. An MLPNN consists of one input layer, at least one hidden layer and one output layer. The MLPNNs involving more than two hidden layers are usually called DNN. The nodes in each layer are fully connected to the nodes in the adjacent layers through weights. The weights between the nodes will be continually adjusted by the training procedure until the model error achieves the minimum. There are a number of training algorithms alternative for efficient training, such as gradient descent algorithm, stochastic gradient descent algorithm, Levenberg-Marquardt algorithm and so on (Shrestha and Mahmood, 2019). In the training process, the difference between the target and prediction can be quantified using the loss function. For various prediction tasks, different loss functions including mean-squared loss, cross-entropy loss and dice coefficient loss can be employed to fit the goal. Once the training of the MLPNN is completed, the output of the MLPNN model can be expressed by the specific mathematical formula. For instance, an MLPNN with one hidden layer and one output neuron can be converted to the following equation.

$$\mathrm{Output}=f_{\mathrm{o}}\left[\mathrm{BO}+\sum\nolimits_{K}\mathrm{W}_{K}f_{\mathrm{H}}\left(\mathrm{BH}_{K}+\sum\nolimits_{i}\mathrm{W}_{i}\ \mathrm{Input}_{i}\right)\right] \tag{1}$$

where f_{o} and f_{H} are the activation functions used in the output layer and hidden layer, BO and BH are the bias for the output layer and hidden layer, W is the weight between the nodes, K is the number of nodes in the hidden layer, and i is the number of the input variables.

While MLPNNs can describe the complicated non-linear relations between the inputs and outputs, it ignores the interdependencies among the input variables. To this end, RNN was designed for solving the time series problems, such as weather forecasting and text processing. As shown in Fig. 1, the unrolling of RNN shows that the neurons in the hidden layer at the current moment not only receive the current input information, but are also affected by the previous information. Each layer of RNN unrolling has the same weight values, which are trained at different times with

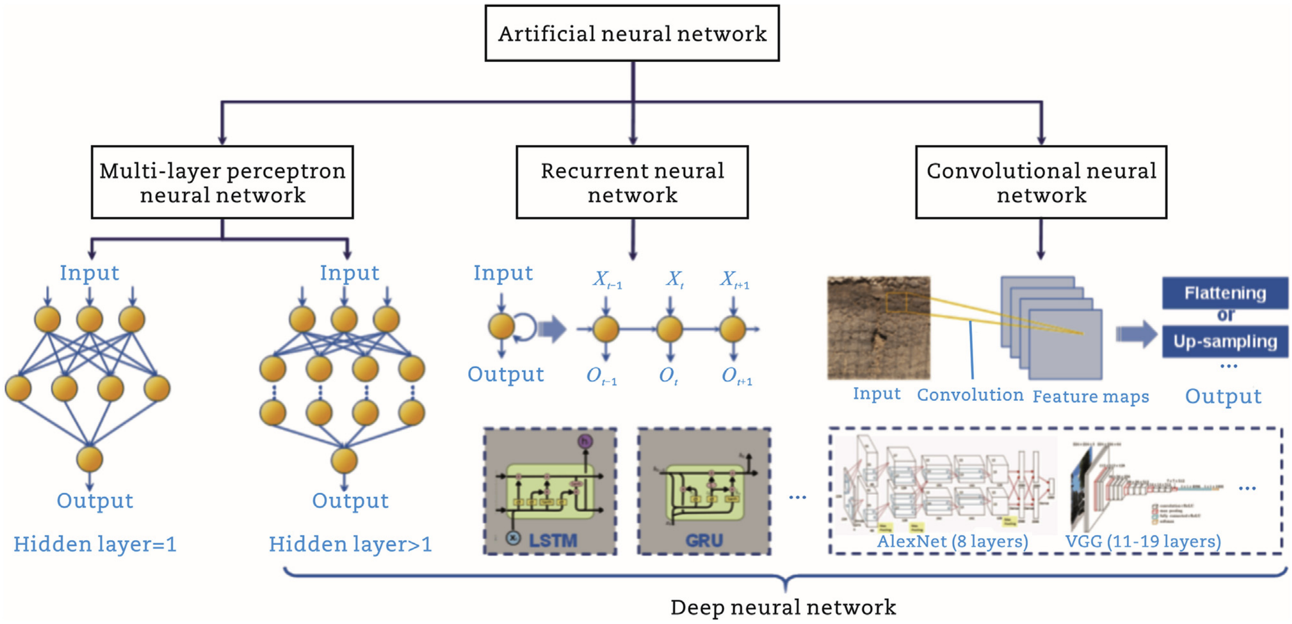

Fig. 1 – Classification of ANNs.

time-related inputs. Long short time memory (LSTM) (Hochreiter and Schmidhuber, 1997) and gated recurrent unit (GRU) (Cho et al., 2014) are the implementations of the RNN. Compared with LSTM, GRU reduces the computational cost while keeping the same performance (Chung et al., 2014). In the field of pavement engineering, it has proven that RNN can effectively capture the patterns of pavement deterioration from the time series data.

CNN was developed to efficiently extract features from two-dimensional (2D) data such as images (Krizhevsky et al., 2012). Unlike ANNs and RNNs that need to flatten 2D data for further processing, CNNs adopt a series of convolution and down-sampling layers to generate feature maps that reflect the key information in the images. Over the past decade, CNNs have made great achievements in the field of computer vision and image recognition (Zhao et al., 2019). Thousands of neural network architectures based on CNN, such as VGGNet (Simonyan and Zisserman, 2014), Resnet (He et al., 2016) and U-net (Ronneberger et al., 2015), have been proposed for object classification, object localization, semantic segmentation and instance segmentation in the image detection (Fig. 2). The pavement distress classification and localization are generally conducted by integrating convolution layers and full connection layers while segmentation tasks are mainly based on the fully convolutional neural network with encoder and decoder sections.

1.2. *Motivation*

After decades of development, ANNs have been successfully applied in various fields. Especially in recent years, with the emerging and boosting of CNNs, DNNs are increasingly the model of choice in many application fields, especially for highly labor-intensive tasks. As an extremely powerful tool, ANN is able to provide a new perspective for the future development of pavement engineering.

Due to the exciting successes in ANNs, a large number of researches have been conducted in terms of using neural networks to enhance pavement performance. Ceylan et al. (2014) have summarized the previous findings on the ANN application in several areas of pavement engineering. However, this work only focused on specific subjects, and did not keep up with the new challenges and changing

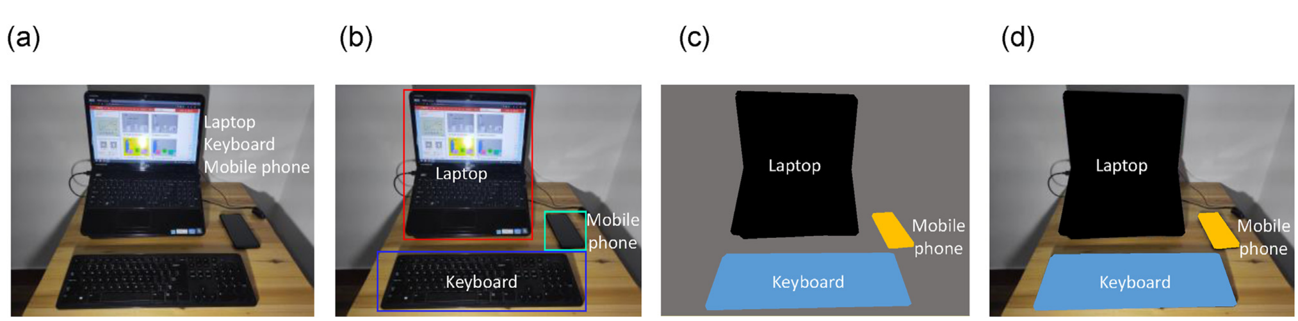

Fig. 2 – Image recognition. (a) Object classification. (b) Object localization. (c) Semantic segmentation. (d) Instance segmentation (Liu et al., 2020a).

situations considering the rise of deep learning from 2012 onwards (MIT Technology Review, 2013). In recent years, many scholars have successfully introduced and developed new useful methods based on DNNs in the field of pavement health inspection and monitoring. This interesting topic has been reviewed several times by researchers such as Zakeri et al. (2017), Xu et al. (2019), Cao et al. (2020) and Hou et al. (2020). However, these state-of-the-art review studies were limited to a specific application, namely image-based pavement surface distress detection. Therefore, there is a great demand for a comprehensive overview of the achievements, major challenges, and future trends in this field.

This study aims to conduct a systematic literature review of how ANNs have been utilized at the different stages of pavement engineering, including pavement design, construction, inspection and monitoring, and maintenance. The topics involved in this paper are listed in Table 1. This study focused on the papers published over the last three decades, especially for the studies conducted since 2013. Such a review can provide a comprehensive and in-depth analysis to identify the new challenges and future research directions, which helps researchers discover where this new technology is applicable.

2. Literature data retrieval method

To achieve our research goal, available papers regarding the application of ANNs in pavement engineering were collected. This review paper covered the papers published in English between January 1992 and September 2020. The literature data was retrieved from the following digital libraries.

- Web of Science.
- ScienceDirect.
- IEEE Xplore.
- Transportation Research Record (TRR).

The primary descriptors used in literature search were generated by combining different keywords (Table 2). After searching the prescribed keywords in the selected databases, the following five steps were adopted to identify

Table 1 – Major subjects involved in this paper.

Major stage	Sub-topic
Pavement design	Structure design
	Asphalt mixture design
	Cement concrete design
Pavement construction	Workability and quality control
	Field performance evaluation
	Cost analysis
Pavement inspection and monitoring	Surface distress classification
	Surface distress localization
	Surface distress segmentation
	Structure inspection
Pavement maintenance	Performance evaluation
	Performance prediction
	Maintenance planning

Table 2 – Keywords used in the literature search.

Category	Keyword
A	Artificial neural network
	Deep neural network
	Convolution neural network
	Recurrent neural network
B	Pavement
	Road infrastructure
	Base course
C	Material design
	Structure design
	Construction
	Compaction
	Cost analysis
	Inspection
	Distress detection
	Performance prediction
	Maintenance and rehabilitation

related papers, which displays in Fig. 3. A total of 683 journal papers and conference papers on this topic were extracted from raw literature data. Fig. 4 shows the distribution of these papers over the last three decades. It can be observed that the number of published papers has a rapid growth in the last ten years. The lower publication number in 2020 is mainly due to the scope of this investigation, which did not cover the period after September 2020. Among the 683 papers, pavement inspection and monitoring has attracted the largest research interest (59.9%), followed by design (20.5%), maintenance (13.3%), and construction (6.3%). In addition, we found that Kasthurirangan Gopalakrishnan, Halil Ceylan, Sunghwan Kim, Kelvin C.P. Wang, Allen Zhang and others are the most active scholars in this field. Given the huge quantity of existing research papers, it is impractical to systematically analyze them all. Therefore, the following criteria were used to select papers for in-depth reviewing.

- The papers with hot research topics such as deep learning, image recognition and novel data annotation and augmentation technology were selected preferentially.
- The papers with significant contributions were selected based on citations, publication time, the novelty of the research methods and data size and quality.
- The journal papers were preferred over conference papers on the premise of the same quality.

Based on these criteria, a total of 143 papers were selected by authors, which will be comprehensively reviewed in the rest of the paper.

3. ANN application in pavement design

Pavement design involves the complex interactions between the material, structure, load and environment. Traditional design procedure relies on experienced engineers and complicated calculations. With the research data in pavement engineering becoming more accessible, researchers have attempted to generate and evaluate design schemes using

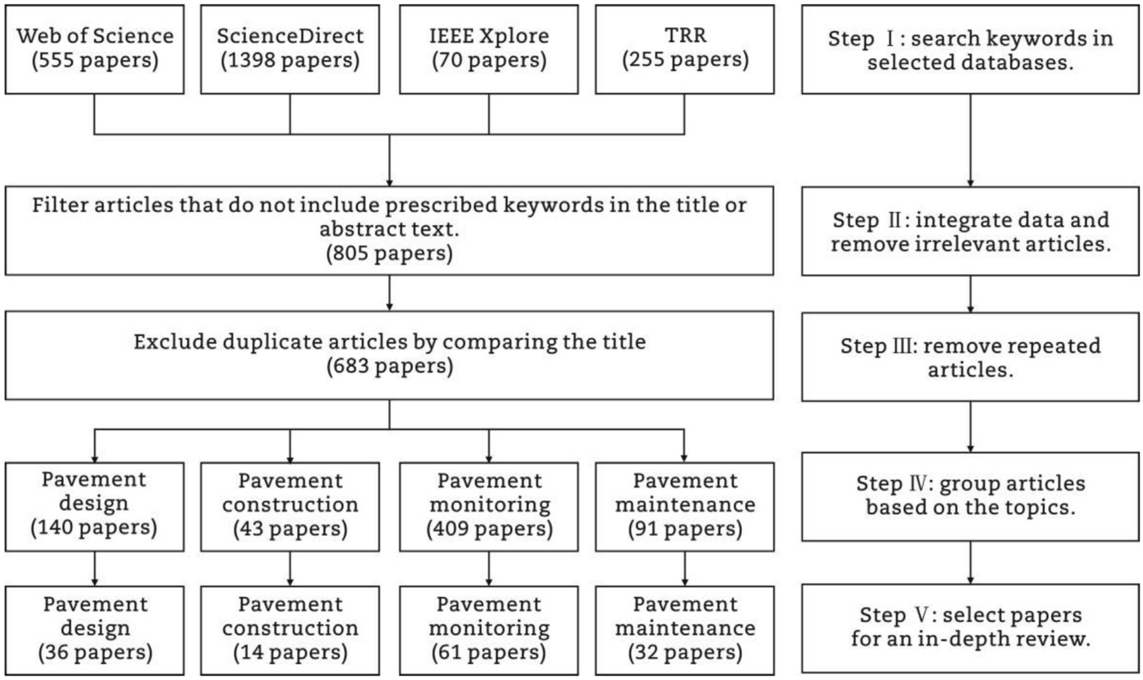

Fig. 3 – Process of literature search and processing.

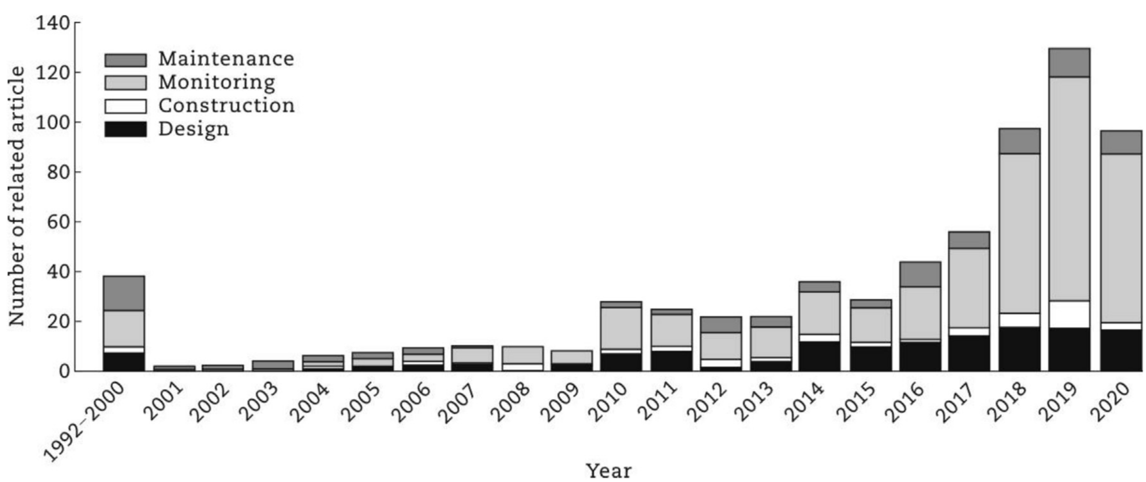

Fig. 4 – Literature search results.

ANNs. As an effective alternative tool, ANNs have begun to change the design procedure. Through the literature review, three research hotspots in the pavement design stage were identified: structure design, asphalt mixture performance prediction and cement concrete performance prediction.

3.1. *Structure design*

Traffic loading data is one of the key elements required for pavement structure design. Equivalent single axle load (ESAL) is widely used to reflect the level of traffic loading, which converts different kinds of vehicle load to a common axle load (AASHTO, 1993). Accurate classification of vehicles is the basis for estimating the number of ESALs. Kwigizile et al. (2005) developed a probabilistic neural network based on the classical Bayes classifier to classify vehicles according to the number of axles, axle spacing, vehicle length, and overall vehicle weight. The ground truth data of this study was obtained by visual classification. In order to integrate the influence of the type of wheel (single and dual) on ESAL calculation, Amorim et al. (2015) presented an MLPNN with two hidden layers to determine the influence coefficient of different axle configurations. Given that the existing mechanics-empirical equation is too complex for design ESAL estimation, Tigdemir (2014) established a direct relationship between the design ESAL and the pavement constitution using MLPNN. Accurate ESAL estimation can provide reliable traffic loading information for structure analysis.

Table 3 – Comparison of different ANN architecture used in asphalt mixture performance prediction.

Reference	Prediction	Material	ANN architecture
El-Badawy et al. (2018)	Dynamic modulus	HMA	Two-hidden-layer MLPNN
Seitllari et al. (2019)	Dynamic modulus	Aging HMA	One-hidden-layer MLPNN
Moussa and Owais (2020)	Dynamic modulus	HMA	CNN
Tapkin (2014)	Fatigue life	Fly ash modified HMA	Three-hidden-layer MLPNN
Moghaddam et al. (2016)	Fatigue life	Polyethylene terephthalate modified HMA	One-hidden-layer MLPNN
Wang et al. (2018)	Fatigue life	Cement emulsified HMA	Two-hidden-layer MLPNN
Ziari and Divandari (2013)	Flow number	HMA	One-hidden-layer MLPNN
Moghaddam et al. (2015)	Cumulative permanent strain	Polyethylene terephthalate modified HMA	Adaptive neuro-fuzzy neural network
Oeser and Freitag (2016)	Stress-strain-time behavior	HMA	RNN with two hidden layers
Mirabdolazimi and Shafabakhsh (2017)	Rutting depth	Forta fiber modified HMA	Three-hidden-layer MLPNN
Majidifard et al. (2019)	Fracture energy	HMA	Three-hidden-layer MLPNN

Another challenge in pavement structure design is the huge complicated and time-consuming calculations for pavement response analysis. To overcome this difficulty, some recent studies made efforts to employ the computationally efficient MLPNN models to replace finite element (FE) analysis. Fakhri and Ghanizadeh (2014) developed a framework based on MLPNN and response describing function to determine the magnitude and shape of the three-dimensional (3D) response pulse at the bottom of the asphalt layer, which provided the basis for pavement design including thickness and stiffness of layers. To enhance the generalization ability of the model, Ziyadi and Al-Qadi (2017) proposed an MLPNN model incorporating a k-fold cross-validation technique to investigate the effect of the wide-base tires on asphalt pavement responses, which accurately predicted the eleven critical pavement responses simulated by the three-dimensional FE (3D-FE) model. In airport rigid pavement design, MLPNN models have been proved to be of great potential for accurate stress prediction within a short time (Kaya et al., 2017, 2018b). However, these studies only attempt to use MLPNNs with a single hidden layer to predict the FE calculation results.

To involve more factors influencing pavement response, deeper neural networks have been applied to describe the non-linear relationship between the inputs and outputs. Ceylan et al. (1999) used an MLPNN with two hidden layers to predict the maximum bending stresses and the maximum vertical deflection in the jointed concrete airfield pavements. The results implied that the mean squared error decreases with the increase of network parameters. Through optimization of the network architecture, Rezaei-Tarahomi et al. (2019) developed MLPNNs with a different number of hidden layers and neurons under different cases to predict the critical pavement responses associated with top-down cracking failure. On the basis of this study, Rezaei-Tarahomi et al. (2020) attempted various MLPNN architectures and training algorithms for accurately predicting the maximum top tensile stress yielded by 156 different airplanes. Overall, the scale of the neural network should be determined according to the complexity of the problems.

3.2. *Asphalt mixture performance prediction*

One important application of ANN techniques at the pavement design stage is the material performance prediction, particularly for modified asphalt mixtures. Table 3 summarizes some recent studies on asphalt mixture performance prediction using different ANN architectures. There are several material properties attracting great interest in these studies, including dynamic modulus, fatigue performance and rutting performance.

While dynamic modulus is a fundamental property for asphalt mixture, it relies on expensive advanced equipment for testing so that it is not easily available. For the asphalt mixtures design and optimization, the tremendous mixtures with varying components are required to be tested to obtain the dynamic modulus. Thus, it is labor-intensive and expensive for each experimental investigation. To improve the efficiency, Kaya et al. (2018a) developed MLPNN-based dynamic modulus prediction models for hot mix asphalt (HMA) and warm mix asphalt (WMA) mixtures, in which the aggregate gradation, asphalt properties and volumetric properties were considered. Seitllari et al. (2019) estimated the dynamic modulus changes of aged asphalt mixture using MLPNN with one hidden layer. Meanwhile, two-hidden-layer MLPNN models were also utilized to predict the HMA dynamic modulus (Barugahare et al., 2020; El-Badawy et al., 2018). In addition to using MLPNN, Moussa and Owais (2020) proposed a deep CNN model with six convolution blocks for HMA dynamic modulus prediction. The convolution block consisted of the convolution layers, batch normalization (BN) layers and ReLU activation layers. However, there is a potential risk for overfitting when the experimental data is very limited.

Fatigue performance of the asphalt mixtures is affected by various factors such as material behavior, climatic environment and traffic loading. With the boosting of the ANNs, some studies have made efforts to develop fatigue performance prediction models for different types of asphalt mixtures. Moghaddam et al. (2016) adopted various machine learning methods including MLPNNs to predict the fatigue life of polyethylene terephthalate modified asphalt mixtures, which proved the feasibility of the use of the neural network for fatigue life prediction. For optimization of the MLPNN architectures, Tapkin (2014) attempted MLPNNs with one, two and three hidden layers to determine the fatigue life of fly ash modified dense asphalt mixtures. In order to consider the different fatigue life test modes, Ahmed et al. (2017) developed two types of MLPNN models for fatigue life prediction of HMA with the strain-controlled tests and stress-controlled tests. The results indicated that the prediction accuracy of the strain test model performed better than that of the stress test model.

Rutting performance is one of the considerable indicators for asphalt mixture design. In order to reduce the time-consuming tests, a number of studies gradually focused on the application of ANNs in rutting performance prediction (Hussan et al., 2019; Shafabakhsh et al., 2015). Mirzahosseini et al. (2011) and Ziari and Divandari (2013) applied MLPNNs to evaluate the rutting potential of asphalt-aggregate mixtures, which correlated the flow number of the Marshall specimen to the asphalt content, aggregate gradations, mixture volumetric properties. Considering the varying load patterns, Hafeez (2018) investigated the effect of waveform loading, truck speed levels and load pulse duration on the permanent deformation of asphalt mixture using MLPNN. For modified asphalt mixtures, Moghaddam et al. (2015) proposed an adaptive neuro-fuzzy inference neural network to predict the cumulative permanent strain of the polyethylene terephthalate modified asphalt mixtures. Through numerical experiments with 1000 MLPNNs, Mirabdolazimi and Shafabakhsh (2017) identified the best three-hidden-layer MLPNN for rutting depth prediction of the forta fiber modified asphalt mixtures.

3.3. *Cement concrete performance prediction*

Modern concrete materials require high durability and strength for long life service. It is crucial to develop new materials and optimize the mix proportion to improve concrete performance. To achieve an accurate prediction of flexural and compressive strength, Fakhri et al. (2017) proposed a genetic algorithm (GA) evolved neural network to estimate roller compacted concrete pavement (RCCP) characteristics with different compositions. The GA was applied in the network training process. In addition, the sensitivity analysis was conducted to identify the effective content for cement, reclaimed asphalt pavement (RAP) and rubber. Differing from the above method of integrating GA, Liu et al. (2020b) first obtained a compressive strength prediction model for polyvinyl alcohol (PVA) fiber-reinforced cementitious composites containing nano-SiO_2 using MLPNN, and then applied GA in the optimization of the mix proportion of the composite materials to maximize the compressive strength. GA, as an optimization algorithm, was widely integrated into the MLPNN development.

Permeability is one of the key factors that influence concrete long-term durability. Some studies have adopted different methods to measure the permeability of concrete, such as rapid chloride permeability test (RCPT) and boil test (BT). Based on these experimental results, the permeability of concrete was predicted by different ANN architectures (Yasarer and Najjar, 2011, 2012, 2014). Given that the shrinkage of concrete may induce cracks, leading to the infiltration of corrosive substances, it is also of great concern for the effective prediction of concrete shrinkage. Bal and Buyle-Bodin (2013) developed an MLPNN model with two hidden layers to effectively predict the drying shrinkage strain of concrete, further analyzing the effect of input parameters on the shrinkage at different ages. Liu et al. (2016a) estimated the autogenous shrinkage of concrete mixtures using MLPNN and support vector machine (SVM), in which the material proportion, curing temperature and hydration age were considered. Using similar input variables as the previous study, Garoosiha et al. (2019) evaluated the performance of MLPNNs with different architectures and training algorithms in the prediction of concrete shrinkage. Overall, MLPNN is an effective and efficient tool to reflect complicated non-linear relations between material performance and composition, which is applicable for most pavement material designs. However, MLPNN is easy to over fit when handling a small experimental dataset. The MLPNN architecture should be elaborately designed for matching the data complexity. In addition, given that the material performance involves various factors, it is critical to optimize the input variables of the MLPNN to learn effective knowledge.

4. ANN application in pavement construction

Compared with the other three stages, fewer scholars focused on the application of ANNs in the pavement construction process. Through the literature review, three topics were identified, including pavement construction quality, material field performance, and cost and energy consumption. The specific studies will be reviewed in this section.

Compaction quality control has significant effects on the deterioration of asphalt pavement. A promising technology is real-time compaction monitoring based on the intelligent roller. Integrating ANNs in asphalt compaction analyzer, Commuri and Zaman (2008) realized automated pavement compaction level classification, which extracted the key features of the vibration signals as the inputs of the ANN. On this basis, a deeper MLPNN with two hidden layers was developed to estimate the stiffness of the subgrade during compaction (Imran et al., 2018). This study calibrated the ANN output (i.e., four different stiffness levels) to obtain the continuous modulus of the subgrade. For the concrete pavement construction process, the slump of concrete plays an important role in construction workability. Öztaş et al. (2006) explored the applicability of ANNs to predict the slump of high-strength concrete, which utilized mix proportion and additive content as the model inputs. Chandwani et al. (2015) developed an MLPNN model incorporating GA to model the relationship between the slump of ready-mix concrete and different design mix proportions, which improved the convergence speed and prediction accuracy of the MLPNN model by using GA for the model weight optimization. In addition to the prediction of the construction workability, the material field performance, such as subgrade soil resilient modulus and granular material strength, is also of great importance for pavement quality.

The resilient modulus of the subgrade soil is not only affected by the routine soil property, but also changeable for environmental conditions. Among various statistical techniques, ANNs are outstanding in resilient modulus prediction (Khasawneh and Al-jamal, 2019; Saha et al., 2018). Nazzal and Tatari (2013) applied a one hidden layer MLPNN model to estimate the subgrade resilient modulus based on soil index properties. In order to improve the prediction accuracy, GA was used in this study to select input variables to minimize the model errors. Given that the soil moisture content and temperature vary with the seasons, Zhang and Yu (2018) estimated the subgrade elastic modulus in different seasons using a two-hidden-layer MLPNN. In addition, some studies measured the strength of the subgrade soils and unbound granular materials by California bearing ratio (CBR) and applied ANNs to predict the field test results (Attoh-Okine and Fekpe, 1996; Ghorbani and Hasanzadehshooiili, 2018).

Evaluation of the construction cost and energy consumption is an essential section for the project cost control and schedule adjustment. The construction cost is affected by material, labor, equipment, and so on. Kaiser et al. (2005) utilized MLPNNs to relate the overall construction cost to the characteristics of the construction and contract, which accurately captured the construction cost trends. He et al. (2014) developed an MLPNN with a comprehensive input of potential influencing factors, including location factors, resource factors and time-related factors, to predict the cost of pavement construction. For the reasonable selection of input variables, Roxas et al. (2019) conducted a correlation analysis to optimize the MLPNN inputs. With the growth of the environmental requirement, energy consumption is also a concern in the construction process. Androjić and Dolaček-Alduk (2018) used MLPNNs to predict natural gas consumption in the process of HMA production, which considered the influence of different asphalt mix types, moisture content, hourly capacity, and production temperature. Meanwhile, the temperature of aggregate is one of the important factors influencing the energy consumption in HMA production. Androjić et al. (2019) proposed an MLPNN model with two hidden layers to estimate the temperature of aggregate stockpiles. The different approaches of aggregate stockpile (i.e., a standard uncovered aggregate stockpile and a solar aggregate stockpile) were taken into account in this study. In summary, MLPNN is the most widely used ANN architecture in the pavement construction stage. For other types of ANNs, such as CNN for image recognition, there are few successful applications in pavement intelligent construction. It is promising to integrate various ANNs in pavement construction safety and management.

5. ANN applications in pavement inspection and monitoring

In addition to the exposure to the natural environment, pavements are expected to support a substantial amount of traffic loading during the operation stage. To maintain pavement in good condition, it is imperative for road agencies to effectively assess pavement condition to arrange appropriate maintenance. From the literature review, pavement surface distress detection is mainly based on images including 2D images, 3D images and thermal images while structure inspection relies on data from ground penetrating radar (GPR) or falling weight deflectometer (FWD). Given the different features of the data from various sensors, different ANN architectures have been applied to address practical issues.

5.1. *Pavement surface distress classification*

Pavement surface distress classification, which aims to automatically recognize the distress type on each surface image, has been an active research topic since the 1990s. With the development of deep learning, the classification methods based on ANNs have changed significantly. Overall, the pavement distress classification methods can be divided into two main frameworks, namely, semi-automated classification framework with pre-defined feature extraction and automated classification framework with active feature extraction (Fig. 5).

Before the rise of deep learning, pavement surface distress classification mainly relied on MLPNNs. The largest challenge for the MLPNN based classifications methods was the image feature extraction. To this end, a number of pre-defined feature extraction techniques based on image processing were adopted to extract the key features on the image as the inputs of the MLPNN. Chou et al. (1994) used a three-layer MLPNN to classify the different types of pavement distresses. The model received moment invariants calculated from different types of distress as inputs. In order to reduce the redundant information, Xu et al. (2008) proposed two feature parameters (cracking rate and minimum external rectangle of the crack) to reflect the useful information in the crack images. Based on the pre-defined feature parameters, an MLPNN was constructed to distinguish alligator crack and linear crack. Considering different features of various distress types, distress tiles distribution was introduced to provide effective features for MLPNN classifiers (Salari and Bao, 2011; Salari and Yu, 2011; Yu and Salari, 2011). While the pavement distress classification can be completed using the semi-automated classification framework, it is vulnerable to pre-defined feature extraction approaches, leading to inapplicability in changeable circumstances.

In recent years, CNN has been proved highly competitive in image classification, which is widely used in the automated classification framework. The most promising feature of CNN is the automated feature engineering so that it can be self-adapting for varying classification tasks. Using the images captured by a car black box camera, Park et al. (2019) attempted different CNN architecture with varying convolution layers and filter sizes to classify the elements of each road surface into three categories, including cracking, road marking, and intact area. Based on the transfer learning method, Yang et al. (2020a) utilized visual geometry group (VGG) network connecting an MLPNN for automated crack classification, which achieved high accuracy in public datasets. In order to further improve the performance of CNN based classifiers, 3D distress images were used to enhance the distress feature while reducing the noises. Then, different sizes of receptive fields were investigated to select optimal hyper-parameters for CNNs (Li et al., 2020; Zhou and Song, 2020). It can be certain that the automated classification framework based on CNN can achieve perfect accuracy under the premise of sufficient labeled data. However, recent studies are more interested in distress localization and segmentation.

5.2. *Pavement surface distress localization*

Pavement surface distress localization aims to determine the location of the detected object on the image. There are two

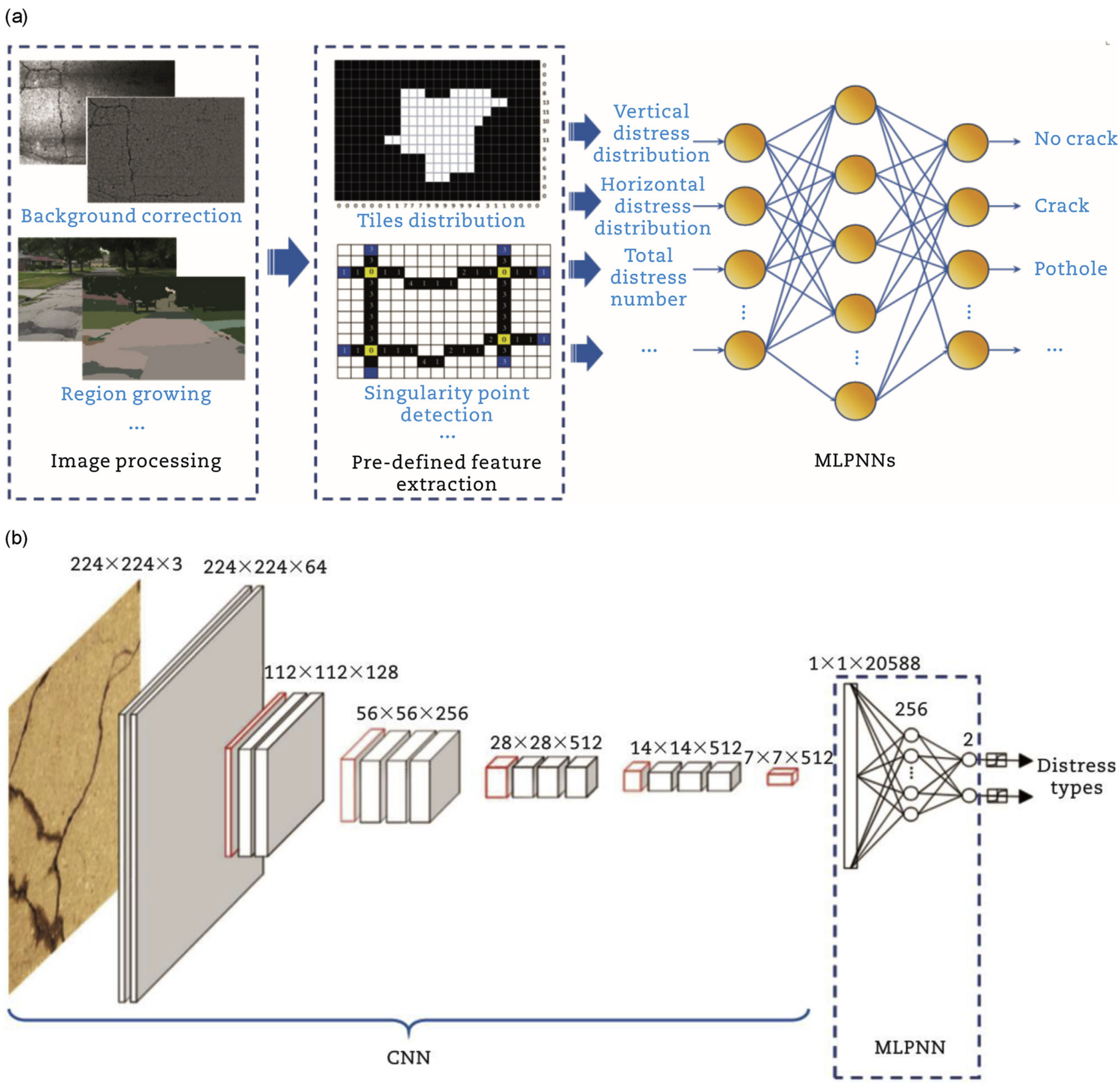

Fig. 5 – Pavement surface distress classification framework. (a) Semi-automated classification framework with pre-defined feature extraction. (b) Automated classification framework with active feature extraction (Yang et al., 2020a).

localization methods based on CNN available for this issue, that is, region proposal based CNNs (two-stage method) and end-to-end CNNs (one-stage method). The region proposal based CNNs, such as region-based CNN (R-CNN) (Girshick et al., 2014), fast R-CNN (Girshick, 2015) and faster R-CNN (Ren et al., 2016), depend on the region of interesting (ROI) to complete object classification and localization. To achieve much faster localization, end-to-end CNNs were proposed to directly predict the object location, such as you only look once (YOLO) (Redmon et al., 2016) and single shot multibox detector (SSD) (Liu et al., 2016b). These methods have been successfully applied in pavement surface distress localization (Fig. 6).

While R-CNN has been introduced for object localization since 2014, it was not designed for pavement distress detection originally. In recent years, faster R-CNN, which developed from R-CNN, was adopted for pavement distress detection. Huyan et al. (2019) developed a CrackDN based on faster R-CNN architecture to detect sealed and unsealed cracks under complex road backgrounds, which considered the influences of unbalanced illuminations, markings and shadings. In addition to application in crack detection, Song and Wang (2019) utilized faster R-CNN to locate various pavement distresses including crack, pothole, oil bleeding and dot surface autonomously. However, the region proposal based CNNs, even using faster R-CNN, could not satisfy the demand for real-time localization (Ibragimov et al., 2020).

Compared with faster R-CNN, YOLO architecture is more widely used in pavement distress localization due to its

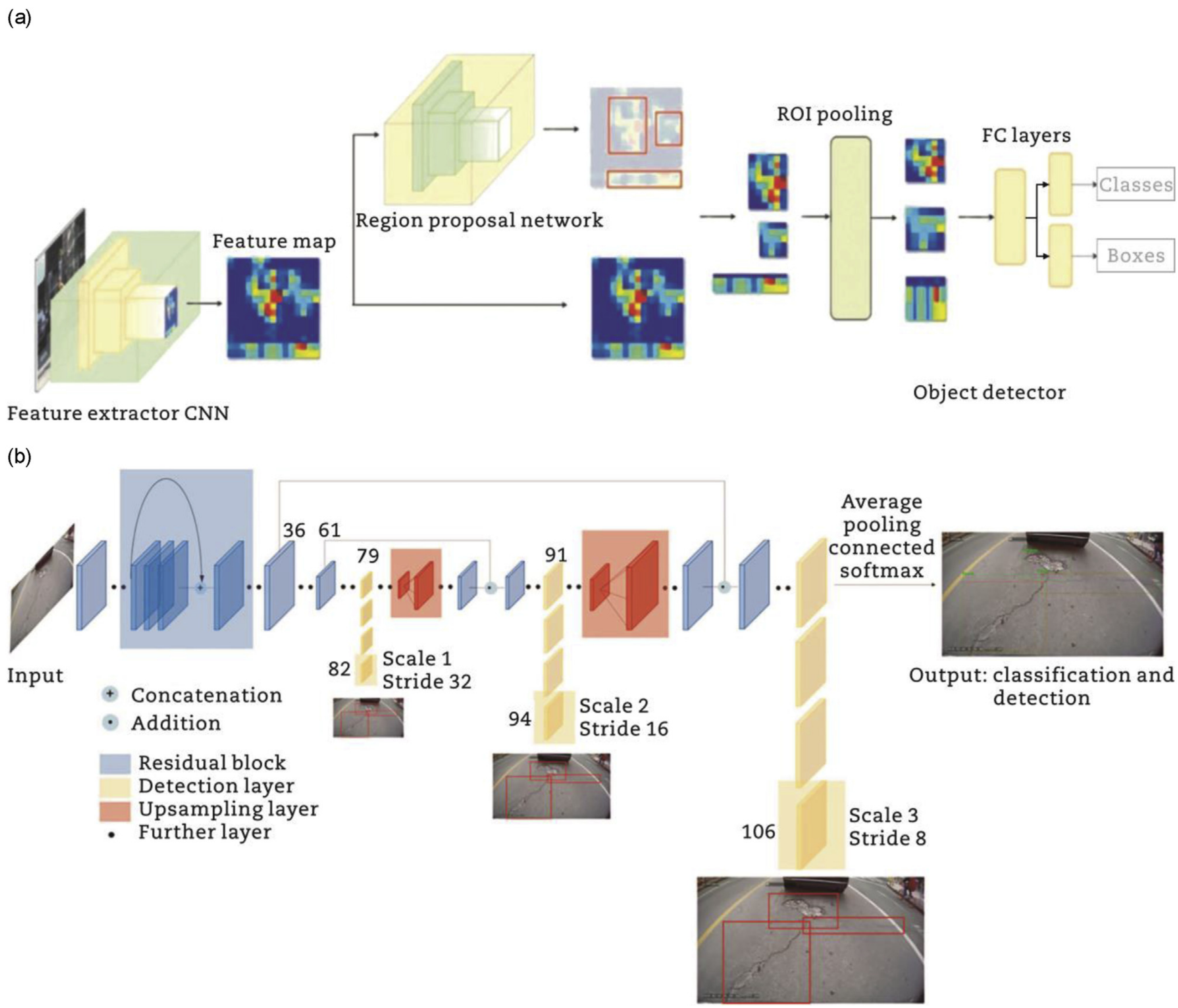

Fig. 6 – Object detection network. (a) Faster R-CNN architecture (Hui, 2018). (b) YOLO v3 architecture (Du et al., 2020).

outstanding computational efficiency (Dhiman and Klette, 2020; Mandal et al., 2018; Majidifard et al., 2020). Du et al. (2020) conducted a comparison between faster R-CNN and YOLO version 3 (v3) to evaluate the detection performance of pavement distress in terms of localization accuracy and processing speed. The results showed that YOLO v3 is 9 times faster than faster R-CNN while keeping the same accuracy. To reach a compromise between accuracy and speed, Ukhwah et al. (2019) adopted multiple YOLO architecture with different backbone networks, including YOLO v3, YOLO v3 tiny, and YOLO v3 spatial pyramid pooling (SPP). In addition, SSD was also used for fast pavement distress detection with low computational efforts. Maeda et al. (2018) developed a smartphone application program embedding SSD architecture for road damage detection, which achieved an inference time of 1.5 s per image on a smartphone. This study demonstrated the feasibility of applying deep learning to locate pavement distress on mobile devices. Using thermal images, Gupta et al. (2020) developed an automated pothole detection system based on modified ResNet34-SSD architecture to detect pothole.

The localization methods based on CNN showed great promising in pavement distress detection, which achieved satisfying accuracy as well as high processing speed. However, the shortcoming of the current methods is the high data size requirement. The datasets used in model training should cover a variety of circumstances to improve the robustness.

5.3. *Pavement surface distress segmentation*

Pavement surface distress segmentation can be viewed as pixel-level distress localization, which aims to separate distress pixels from the background. The CNN architecture used for segmentation tasks generally consists of a downsampling section and an upsampling section to extract features and recover information. Table 4 summarizes the test result of existing methods on the CrackForest dataset (CFD). Based on fully convolution network (FCN), some recent

Table 4 – Test results on CFD dataset.

Reference	ANN architecture	F1 score
Jenkins et al. (2018)	U-net	0.8727
Nguyen et al. (2018)	U-net	0.8745
Fei et al. (2020)	CrackNet-V	0.8918
Mei and Gul (2020)	ConnCrack	0.9196
Fan et al. (2018)	CNN	0.9244
Zhang et al. (2020a)	Split-attention networks	0.9521
Lau et al. (2020)	U-net	0.9555
Liu et al. (2020a)	U-net	0.9575

studies made efforts to develop automated pavement distress segmentation algorithms for 2D images (Bang et al., 2019; Chen et al., 2020; Ren et al., 2020).

Liu et al. (2019) proposed a deep hierarchical CNN based on FCN and the deeply-supervised nets (DSN) to integrate multi-scale and multi-level features for pixel-level segmentation. Similarly, Yang et al. (2020b) designed a novel FCN architecture, called feature pyramid and hierarchical boosting network (FPHBN), for pavement crack segmentation, which integrated semantic information from high-level layers to enrich the low-level feature. To incorporate the uncertainty in the features, Tong et al. (2020a) developed an uncertainty framework based on FCN and Gaussian-conditional random field (G-CRF) for pavement defect segmentation. In this framework, G-CRF is utilized to refine the segmentation generated by FCN. While using 2D image based FCN is a low-cost and simple way for pavement distress detection, its segmentation accuracy is greatly affected by the environmental conditions (e.g., shadow, surface color, and illumination intensity), especially for the tiny shaped pavement crack detection.

Compared with 2D images, 3D images are less vulnerable to environmental changes, providing more useful information as well as fewer noises for the distress segmentation (Li et al., 2019; Zhang et al., 2018; Zhou and Song, 2020). Some scholars have combined the deep learning and 3D imaging technique for crack segmentation. Zhang et al. (2017) developed an efficient CNN architecture called CrackNet for pixel-level pavement crack detection, which replaced pooling layers by convolution layers with larger strides. Inspired by CrackNet, Fei et al. (2020) proposed a deeper architecture CrackNet-V for segmenting pavement crack on 3D asphalt pavement images. Through stacking convolution layers, CrackNet-V reduced the parameters while achieved effective feature extraction. In addition to CNN, RNN was attempted for crack segmentation. Zhang et al. (2019) proposed an RNN architecture CrackNet-R based on gated recurrent multilayer perceptron (GRMLP) to conduct crack segmentation. This network is four times faster than the original CrackNet. However, these studies need thousands of 3D images for model training, which is expensive in 3D image acquisition and annotation.

Given the limitations of training data, U-net architecture was used to complete crack segmentation tasks with a much smaller training set. König et al. (2019) developed a fully convolution U-net based architecture using three shortcut connection layers for semantic crack segmentation, which allows for the use of small datasets. Huyan et al. (2020) modified U-net to develop a pixel-wise crack detection architecture CrackU-net, which greatly outperformed both FCN and traditional U-net in terms of accuracy. To reduce the computational efforts, Chen et al. (2019) introduced a switch module into U-net, which can skip the decoder section to save computation time when no cracks identified. In addition, Pereira et al. (2019) develop a road condition monitoring system incorporating U-net for pothole segmentation. However, most of the studies focused on crack segmentation while ignoring the application in other types of pavement distresses.

Unlike pavement distress localization, it is difficult to achieve real-time distress segmentation due to its high computational costs. Therefore, as shown in Fig. 7, several studies proposed a two-step segmentation method to improve processing speed (Kang et al., 2020; Liu et al., 2020a). In this framework, pavement distress segmentation was conducted within the bounding box generated by the localization, which reduces the computation time spent in non-distress areas. This work provided a new perspective for rapid pavement distress segmentation.

5.4. *Pavement structure inspection*

Non-destructive test (NDT) methods have been widely employed to evaluate the pavement structure condition. Among various pavement structure inspection approaches, FWD and GPR are two common testing equipment for rapid and high-frequency data collection. After acquiring the testing data, various data mining methods can be used to extract useful information to assess the pavement structure health. ANN, as an effective tool, is applied to estimate the pavement deflection as well as interface conditions.

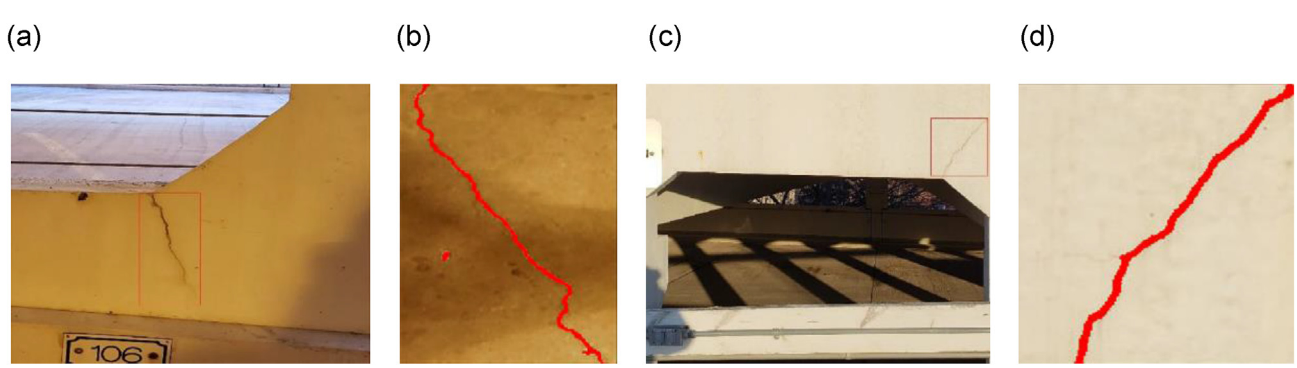

Fig. 7 – Pavement distress segmentation based on two-step method (Kang et al., 2020). (a) Object detection stage (example 1). (b) Segmentation stage (example 1). (c) Object detection stage (example 2). (d) Segmentation stage (example 2).

Pavement modulus back-calculation is a critical technique to evaluate the pavement structure health using FWD deflection bowl parameters. Based on the FWD measurements and layer thicknesses, many studies utilized MLPNNs to predict the modulus of the asphalt concrete layer, base and subgrade (Gopalakrishnan et al., 2013; Leiva-Villacorta et al., 2017; Mousa et al., 2019; Saric and Pozder, 2018). Gopalakrishnan (2010, 2012) and Gopalakrishnan and Kim (2010) integrated various optimization algorithms including particle swarm optimization (PSO), shuffled complex evolution (SCE) and GA with MLPNN models to predict pavement layer modulus, providing a novel hybrid back-calculation system. To provide a simple approach for pavement structure evaluation, Fakhri and Dezfoulian (2019) and Lee et al. (2019a) utilized MLPNN to establish a relationship between pavement surface conditions and FWD deflections.

GPR has been widely employed to inspect pavement structure distress, such as reflection crack, asphalt layer stripping, and uneven settlement. Given the difficulty of identifying the defects from GPR images, a number of studies have begun to apply deep learning in automated distress detection. Some of the studies extracted the time-frequency feature vectors from GPR signals using various data processing methods. Then, MLPNN-based recognition algorithms were designed for automated detection tasks, including moisture damage detection and asphalt pavement density monitoring (Shangguan et al., 2014; Zhang et al., 2020b). Tong et al. (2020b) utilized a deeper MLPNN architecture to directly extract the feature from GPR signals, subsequently identifying the abnormal signals and internal defects. Compared with MLPNNs, CNNs are more suitable for processing GPR images (Fig. 8). Based on the GPR images, Tong et al. (2018) developed two CNNs called multi-stage CNN and cascade CNN to classify the subgrade defects in each sliding window. Gao et al. (2020) proposed a CNN-based deep learning architecture faster R-ConvNet, to detect and locate the reflection cracks, water-damage pits, and uneven settlements by bounding boxes. In addition, to further calculate the crack volume and predict the growth tendency of cracks, Tong et al. (2017) developed three different CNNs for automated pavement concealed crack recognition, location, and feature extraction, respectively. ANNs greatly improve the efficiency of automated GPR image detection, overcoming the limitations of relying on experienced engineers in traditional manual detection.

6. ANN application in pavement maintenance

Given the conflict between growing maintenance demand and insufficient maintenance fund, the practical and comprehensive management for road infrastructure is imperative. Pavement performance evaluation and prediction is a prerequisite step for the maintenance and rehabilitation (M&R) arrangement. Considering the powerful nonlinear mapping ability of ANNs, various ANNs have been applied in pavement performance evaluation and prediction as well as M&R decision-making.

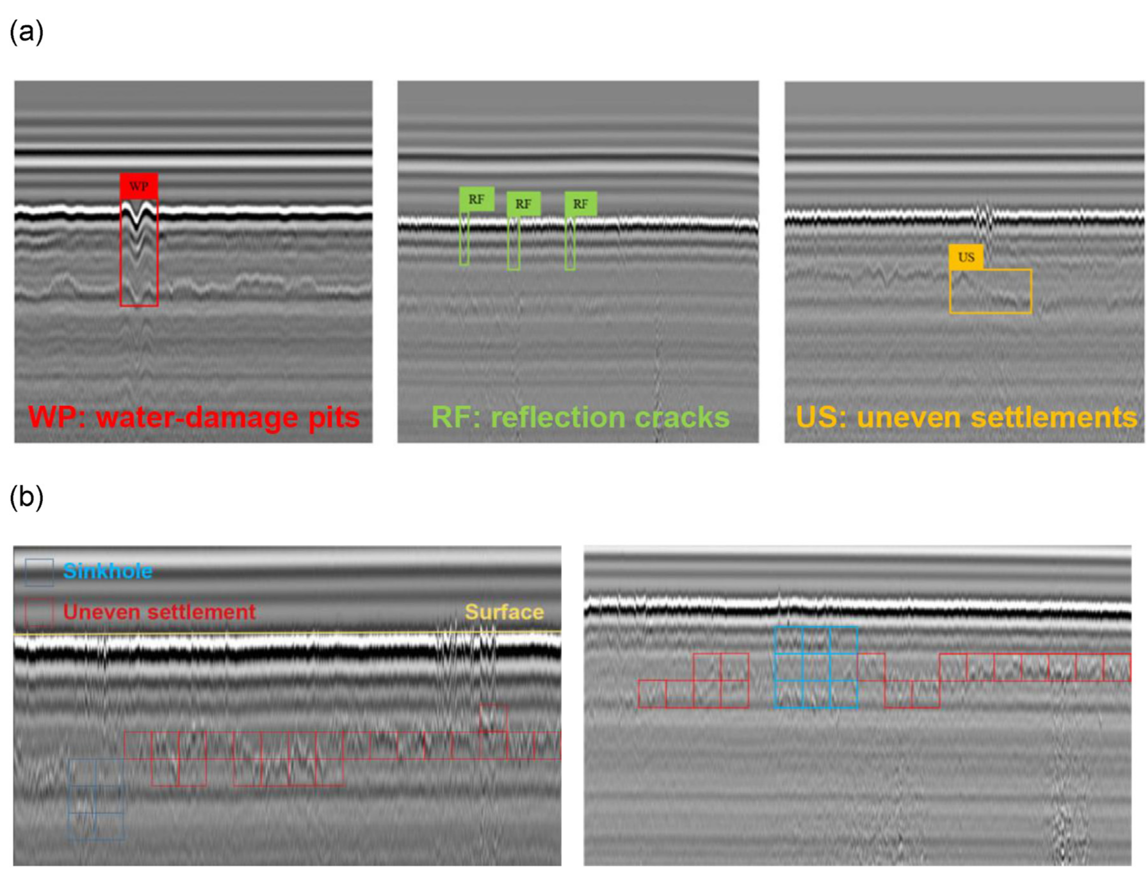

Fig. 8 – Recognition results based on CNN. (a) Region based classifier (Gao et al., 2020). (b) Sliding window based classifier (Tong et al., 2018).

6.1. *Pavement performance evaluation*

With respect to pavement performance evaluation, recent studies have utilized ANNs to explore the relationship between different performance indicators, further establishing the comprehensive evaluation system. It is meaningful to analyze the interaction between a variety of pavement distress, helping with the pavement design and maintenance.

Pavement roughness is a critical factor for vehicle operating comfort and safety. Some studies have successfully used MPLNNs to establish the relationship between international roughness index (IRI) and other types of distress parameters like rutting, cracking, raveling, and potholes (Aultman-Hall et al., 2004; Chandra et al., 2013). Apart from the pavement surface defects, pavement structure conditions are also considered as a key factor that influences the IRI (Luca, 2020). Therefore, Dong et al. (2019) developed a T-S fuzzy neural network (FNN) to estimate the damage condition of a cement-stabilized base, in which the crack depth, breadth and lumpiness were considered.

In order to conduct a more systematic evaluation for pavement conditions, some studies made efforts to establish an evaluation system using ANNs. Huang et al. (2012) proposed a pavement condition evaluation model based on the radial basis function (RBF) neural network to determine the pavement health score. Hu et al. (2012) utilized self-organizing feature map neural network (SOMNN) to develop an evaluation method with comprehensive consideration of four affecting factors including pavement condition, ride quality, structure bearing capacity and skid resistance. The weights of the ANN represent the contribution of sub-indicators in the comprehensive evaluation system.

6.2. *Pavement performance prediction*

There are a variety of factors influencing pavement deterioration, involving pavement age, material property, climate environment, traffic loading, and maintenance history. Long-term pavement performance prediction is of significance for pavement maintenance decision-making. However, the input variable selection strategy has great effects on the performance of ANNs. Different ANN-based prediction models with varying inputs are listed in Table 5.

According to the time attributes of the selected variables, the pavement performance prediction models can be divided into static models and dynamic models (Marcelino et al., 2019; Yang et al., 2003), which can be described as the following form, respectively.

$$C_t = f(X_t, t) \tag{2}$$

$$C_t = f(C_{t-n},\ C_{t-n+1}, \cdots, C_{t-1}, X_{t-n}, X_{t-n+1}, \cdots, X_{t-1}) \quad n = 1,\ 2,\ \cdots,\ t-1 \tag{3}$$

where C_t is the pavement condition at age t, X_t is the external variables at age t, such as material property, climate environment, traffic loading, maintenance history, and so on.

The static models only focus on the influencing factors in the current year while do not use the historical pavement performance data. To estimate the probability of alligator crack initiation following M&R treatments, Karlaftis and Badr (2015) proposed a GA-MLPNN model with static inputs including the construction and rehabilitation data, climate data and traffic data. Using similar input variables, Yao et al. (2019) develop five MLPNN models for the prediction of transverse cracking, rutting, roughness, skid resistance, and pavement surface distress, which further integrated principal component analysis (PCA) to reduce the dimension of traffic variables. Similarly, many other studies applied ANN-based static models to predict various pavement indicators, such as pavement condition index (PCI) (Amin and Amador-Jimenez, 2017; Shahnazari et al., 2012) and IRI (Nguyen et al., 2019; Yamany et al., 2020). However, ANN-based static models are not suitable for long term forecasting considering the dynamics of the deterioration process over time.

Through incorporating the time-series data, dynamic models can be used to describe time-dependent processes. The

Table 5 – Summary of the studies applying ANNs to pavement performance prediction.

Reference	Model	Output	Input variable						Model type
			Age	Material	Climate	Traffic	M&R	History	
Karlaftis and Badr (2015)	GA-MLPNN	CP	√	√	√	√	√		Static
Ziari et al. (2016)	MLPNN	IRI	√		√	√			Static
Amin and Amador-Jimenez (2017)	MLPNN	PCI	√	√		√			Static
Fathi et al. (2019)	RF-MLPNN	ADI	√	√					Static
Yao et al. (2019)	PCA-MLPNN	IRI/RD/SFC/TCEI/PDCI	√	√		√	√		Static
Yamany et al. (2020)	MLPNN	IRI	√		√				Static
Yang et al. (2003)	MLPNN	CI/RT/RI	√					√	Dynamic
Yang et al. (2006)	MLPNN	CI	√			√	√	√	Dynamic
Okuda et al. (2018)	RNN	RD	√			√	√	√	Dynamic
Inkoom et al. (2019)	MLPNN	CR	√	√		√	√	√	Dynamic
Choi and Do (2020)	LSTM	RD/CR/IRI			√	√		√	Dynamic

Note: GA-MLPNN means genetic algorithm MLPNN, RF-MLPNN means random forest MLPNN, PCA-MLPNN means principal component analysis MLPNN, CP means cracking probability, PCI means pavement condition index, ADI means alligator deterioration index, RD means rutting depth, SFC means sideway force coefficient, TCEI means transverse cracks rating index, PDCI means pavement distress condition index, PDCI means crack index, RT means rut index, RI means ride index, CR means crack rating.

main dynamic forecasting strategies applied in pavement performance prediction are the MLPNN-based dynamic modeling and RNN-based dynamic modeling. Some studies used MLPNNs with time-series inputs to improve the accuracy of pavement performance prediction (Georgiou et al., 2018; Inkoom et al., 2019; Yang et al., 2003). However, traditional MLPNNs cannot reflect the relationship between input variables, leading to an isolated understand for time-dependent data. Therefore, RNN was designed for effectively capturing long-term dependencies. Okuda et al. (2018) proposed a prediction interval estimation method based on RNN and bootstrap method for rutting depth prediction, which reduced the computation efforts. LSTM, as an advanced RNN architecture, has been applied in pavement performance prediction. Lee et al. (2019b) utilized RNN-LSTMs with different sequence lengths to predict the crack rate, rutting depth and IRI. The independent variable set consisting of ESAL, traffic volume, temperature, precipitation and inspection were input into the model in the form of a time sequence.

While some existing studies have adopted historical data as the inputs of ANNs, some redundant variables may lead to over fitting issues, which in turn reduce the prediction accuracy. To handle this problem, some of these studies further analyzed the importance of inputs using sensitivity analysis so as to select reasonable variables (Fathi et al., 2019; Karlaftis and Badr, 2015; Kargah-Ostadi and Stoffels, 2015; Yao et al., 2019; Ziari et al., 2016). On the other hand, statistics such as growth rate can replace raw data as the model inputs.

6.3. *Pavement M&R planning*

Pavement M&R involves a substantial amount of investment, which has significant impacts on the public. With the expanding road network and growing traffic, more and more attention has been paid to the decision-making methods for pavement M&R either at the project-level or network-level. The M&R decision-making aims to allocate reasonable M&R activities for pavement segments according to the pavement conditions and other goals. Given that the M&R planning has become increasingly complicated, ANNs have been applied in the M&R activity arrangement.

Early in the 1990s, ANN was initially employed to determine the priority of highway pavement maintenance needs, showing its feasibility in network-level maintenance planning (Fwa and Chan, 1993). While the ANN-based ranking method can identify which road segment should be maintained first, the agencies cannot obtain practical treatment recommendations for a specific road segment. To achieve a more detailed M&R planning, Hafez et al. (2019) utilized MLPNN to select appropriate M&R treatments for low-volume roads, which covered different levels of treatments from sealing to overlay. Similar studies were conducted to optimize M&R strategy considering a wider range of affecting factors, such as pavement distress severity, traffic loading and functional class (Domitrovic et al., 2018; Elbagalati et al., 2018; Milad et al., 2020). In addition to matching M&R treatments based on pavement conditions, Bosurgi and Trifirò (2005) proposed a GA-MLPNN based model to search for an optimal M&R strategy for minimizing road accidents, which evaluated the fitness of the solutions using MLPNN.

Maximizing cost-effectiveness is one of the considerable objectives for pavement M&R strategy optimization. Shehab and Meisami-Fard (2013) developed a cost-estimating model for rubberized asphalt pavement rehabilitation projects using MLPNN, which mainly considered the consumption of the various materials. For the purposes of long-term planning and budgeting, Woldemariam et al. (2016) compared the performance of MLPNNs and traditional statistical models in terms of annual maintenance expenditure prediction, displaying the outstanding performance of MLPNNs. Considering the pavement structures and materials, traffic loadings, maintenance records and pavement conditions, Yao et al. (2020) presented deep reinforcement learning (DRL) to obtain a better strategy to improve the long-term maintenance cost-effectiveness.

Compared with long-term M&R planning, short-term M&R planning pays more attention to the effect of the M&R scheme on traffic. Adeli and Jiang (2003) proposed an adaptive neuro-fuzzy logic model for the prediction of the freeway work zone capacity. On this basis, Karim and Adeli (2003) estimated work zone capacity and queue using radial basis function ANN, providing an intelligent approach for work zone design. Based on the extracted congestion characteristics obtained from the mesoscopic-wavelet model, Ghosh-Dastidar and Adeli (2006) used MLPNN to track the travel time of each individual vehicle for further estimating traffic delay and queue length at work zones. However, few recent studies employed ANNs for short-term M&R planning.

7. Existing problems and research prospects

Over the past three decades, tremendous advancements in the field of ANNs have made great contributions to pavement engineering. The existing studies have successfully applied various ANN architectures into the pavement life cycle, including pavement design, construction, inspection and monitoring, and maintenance. While the powerful applicability of ANNs has been proved in solving complicated engineering problems, there are still some issues that need to further investigate in practical application.

7.1. *Data collection and evaluation in laboratory and field tests*

ANN, as a data-driven method, critically relies on a comprehensive and representative database. In recent years, more and more test devices and methods are available for road material and pavement performance evaluation. While various test data are generated in the process of the pavement design and inspection, the data available in a single project is insufficient for completing data mining. However, for the datasets from different studies, there are differences in data records, leading to only partial data being utilized for model training. For example, HMA dynamic modulus is affected by a variety of factors, such as aggregate gradation, asphalt content, test temperature and frequency, and so on, but the data from the different sources have varying experimental variables, which cannot be combined directly for training a dynamic modulus prediction model (El-Badawy et al., 2018).

Therefore, it is imperative to establish a uniform standard or system for digital data collection and storage. To achieve reasonable data to input the model, the data quality should be evaluated from different aspects, such as data size, distribution, and other statistics. Based on the evaluation of the data quality, ANN models with different architectures can be developed to match different data features. Meanwhile, public databases regarding these research topics should be created to promote the application of ANN in the field of pavement engineering.

7.2. Low-cost data annotation for deep neural network

The ANN models used in existing studies are in the category of strongly-supervised learning, requiring extensive prior knowledge. However, data annotation is labor-intensive and time-consuming, and sometimes highly professional labors are needed, particularly in the field of image recognition. On the one hand, pixel-level annotation of the pavement crack image is labor-intensive so that it is challenging to obtain a large dataset. On the other hand, some data formats, such as 2D/3D GPR data, require professional knowledge to obtain the ground truth of the defects. To verify the labeled ground truth, destructive testing methods may be applied to inspect pavement internal conditions. Hence, how to reduce the data requirements and improve the efficiency of the data annotation is a significant task for future deep learning.

ANN-based weakly-supervised learning can be introduced to reduce the requirements of the manually annotated data. Firstly, weakly-supervised learning can identify highly valuable data for annotation. Secondly, it can actively learn new information to promote the model to become stronger. From the perspective of improving the efficiency of data annotation, integrating the pre-training model and annotation fine-tuning is a novel approach for extremely large datasets. The initial data annotation can be automatically conducted by the pre-training model, which can reduce the overall annotating effort.

7.3. CNN-based image processing technology for pavement construction monitoring

Existing studies have adopted MLPNNs to control pavement construction quality and evaluate the project cost. With the improvement of the construction industry, pavement construction safety and productivity are of great concerns. On the one hand, collisions between operating vehicles and workers are the leading source of fatal incidents. On the other hand, real-time monitoring data of construction machinery can help effectively manage the progress of construction. However, there is still no study incorporating CNN-based image processing technology to achieve intelligent pavement construction monitoring.

Based on video data, object detection and tracking can be conducted using CNNs. To reduce the risk of collisions between construction machinery and workers, the camera can be mounted on construction machinery to achieve real-time detection and tracking for workers. Meanwhile, a more economical approach is to use a single camera to monitor the construction area. In addition to preventing collisions by target detection and tracking, action recognition can be conducted to identify the operating state of construction machinery, such as move, stop, work, and so on. Once the operating state of the machine is determined, the workload of different construction machinery can be estimated to evaluate the construction progress and efficiency.

7.4. Generalization performance of ANN-based pavement distress detection

The nonlinear mapping ability of ANNs can be easily changed through adjusting network architecture and hyper-parameter. However, unreasonable ANN architecture will lead to over-fitting or under-fitting for a practical problem. For example, deeper CNNs are continuously developed for pavement distress detection. While much deeper networks are more capable to capture the characteristics of the training dataset, it may lose the transferability for a practical changeable environment due to the defect irregularities, illumination variations, and other influencing factors. Therefore, both accuracy and robustness should be considered when conducting automated pavement distress detection.

Although 3D images are less vulnerable to environmental conditions, few studies have developed the ANN architecture specifically for 3D images. It is anticipated that deep learning incorporating 3D imaging technology can improve the generalization and robustness as well as computational efficiency. On the other hand, various advanced data mining techniques, such as generative adversarial nets, bagging algorithm and boosting algorithm, can be integrated to combat over-fitting issues. Considering the real application scenarios, the generalization performance of the ANN model directly determines whether automated pavement distress detection can be widely applied.

7.5. ANN-based spatial-temporal model for pavement M&R decision-making

Pavement M&R decision-making focuses on the problem of when and what maintenance activities should be carried out to which road section. While a number of studies have utilized ANN to solve this problem, they generally separate the temporal dimension from the spatial dimension. For example, LSTM has been used to predict pavement deterioration while MLPNN has been used to determine the M&R priority of the road segment. However, the interdependency of the road network has a great effect on pavement deterioration and M&R planning.

To this end, Conv-LSTM, as a novel ANN model, has been gradually used in spatial-temporal prediction, such as precipitation, traffic congestion, and so on. This network combines CNN and LSTM to extract spatial-temporal features. It has potential application in pavement performance monitoring at the network level. In addition, pavement maintenance often induces the dynamic fluctuation of traffic in the road network. Therefore, the road network maintenance schedule can further be evaluated to obtain the optimal M&R arrangement using the ANN-based spatial-temporal model.

8. Summary

In this paper, a systematic review for the ANN applications in pavement engineering was conducted, particularly focusing on state-of-the-art research at different stages of pavement engineering. Through literature retrieval in several digital libraries, 683 papers in this field were found and 143 papers were selected for in-depth reviewing. The number of related publications has increased sharply over the past decade. According to these studies, four major research subjects were identified, involving pavement design, construction, inspection and monitoring, and maintenance. Among these topics, ANN-based pavement health monitoring has attracted the largest research interest in recent years.

To handle complicated problems in this field, various ANN architectures including MLPNN, CNN and RNN have been introduced for processing one-dimensional data, two-dimensional data and time-series data. Thanks to the preliminary success of ANN application in the following areas: (1) pavement material composition design, (2) pavement construction quality control and cost analysis, (3) pavement surface and structure defect detection, and (4) pavement performance prediction and maintenance planning, recently, more attention is paid to develop a general ANN-based model for efficiently solving various tasks in pavement engineering. However, challenges obviously remain in terms of data collection, parameter optimization, model transferability and low-cost annotation. It is anticipated that more studies will make efforts to overcome these challenges and explore more cross-disciplinary research fields in neural computing and pavement engineering.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

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