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Review Article

Advanced industrial informatics towards smart, safe and sustainable roads: A state of the art

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HIGHLIGHTS

- The state-of-the-art artificial intelligence algorithm was presented.
- Different non-embedded smart sensors used for road monitoring were summarized.
- Applications of advanced industrial informatics contribute to building a smart, safe, and sustainable road system.

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ABSTRACT

The road is one of the most important civil infrastructures for serving society, where its service quality and life have direct impacts on the safety and comfort of users. Therefore, road construction, condition detection and monitoring, and timely maintenance are particularly important for engineers. Many engineering applications of industrial informatics approaches, like image processing technology, widely used computer-based algorithms, and advanced sensors, have been initially and gradually applied to roads. This state-of-the-art review first summarized the research on industrial applications of advanced information technologies in recent years, while analyzing and comparing the advantages and disadvantages of each technology. Especially, five topics were focused on road construction, road maintenance with decision strategy, road structure evaluation, smart sensing in the road, and cooperative vehicle infrastructure system. It is expected that advanced industrial informatics can help engineers promote the development of smart, safe, and sustainable roads.

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Smart sensing
Cooperative vehicle infrastructure system

1. Introduction

The road is one of the most important civil infrastructures for the development of society. The quality and life of road service can directly impact people's daily life. Therefore, these aspects are important for engineers to solve road problems from road construction, condition detection, monitoring, and timely maintenance.

With the rapid growth of technologies, industrial informatics plays a more and more important role in modern society. Industrial informatics is the combination of information and industry, which is a discipline that introduces information technology (IT) into the process of industrial production, operation, and management. Recently, scholars around the world have carried out extensive research and applied advanced industrial informatics in the construction, maintenance, and management of road infrastructures, which greatly helps extend the service life and improve the service quality of roads. For computer technology, researchers usually combine image processing technology with machine learning or deep learning algorithms (Arya et al., 2021; Chu et al., 2022; Shim et al., 2021; Sun et al., 2022). It was helpful to realize intelligent recognition and detection of road distresses, as well as prediction of basic strain. In addition, some optimization algorithms and models have achieved satisfactory results in road maintenance decision-making (Hafez et al., 2018; Li et al., 2020). In terms of smart sensing, embedded and non-embedded devices have been continuously improved for intelligent monitoring of road traffic, safety, and evaluation (Barriera et al., 2021; Basavaraju et al., 2020). The advantages of these advanced information technologies are as follows. 1) Making industrial applications such as road construction, detection, and monitoring more intelligent and electronic. 2) Replacing part of the artificial processing process, while improving efficiency and reducing costs. 3) It is helpful to assist engineers in completing relevant decisions quickly and accurately. 4) It can promote the construction of energy-efficient, safe, and sustainable road systems to a certain extent. However, there are still some deficiencies in the use and development of these technologies. 1) The use of IT requires road workers to have a professional foundation and experience, such as programming capability and mathematics thinking ability. 2) Research-based on artificial intelligence (AI) requires a large amount of data for model training. It has huge parameters and slow speed, while the accuracy is closely related to the quality of the data set. 3) Although computer algorithms and sensors are relatively mature, they still need innovation and improvement for specific engineering purposes. The above problems need to be solved by engineers.

Advanced industrial informatics has been widely applied in almost every aspect of road engineering, including cost estimation and performance prediction in the early stage and distress detection and maintenance in the later stage. Therefore, relevant algorithms, research, and industrial applications were reviewed and summarized from five aspects: road construction, road maintenance, and decision strategy, road structure evaluation, smart sensing in the road, and cooperative vehicle infrastructure system, which may provide a reference for road engineers. The details are shown in Fig. 1. It is expected that advanced industrial informatics can significantly help engineers to promote the development of smart, safe, and sustainable roads. As these advanced approaches can extend the service life of roads and improve service quality, it is believed that they can help mitigate the carbon footprint to a certain extent.

2. Advanced industrial informatics in road construction

In the early stage of road construction, artificial intelligence (AI) is often used for construction cost estimation, long-term performance prediction, and other tasks. Among them, intelligent algorithms, big data, and deep learning (DL) are mostly concerned by engineers.

2.1. *Artificial intelligence-based algorithms*

AI is a comprehensive discipline that refers to the ability of machines or artificial products to perform the same functions as human thinking, dealing with noise, incomplete data, and nonlinear problems (Kalogirou, 2003). In this section, the applications of genetic algorithms (GA), swarm intelligence (SI), and artificial neural networks (ANNs) are reviewed.

2.1.1. *Genetic algorithm*

Compared with traditional optimization algorithms, GA has many advantages. The two most significant characteristics are the ability to deal with complex problems and parallelism. GA can deal with various types of optimizations, and the population (or any subgroup) can explore the search space in multiple directions at the same time. However, GA also has some disadvantages. The formulation of the fitness function, the use of population size, the selection of important parameters such as mutation rate and crossover rate, and the selection criteria of the new population should be carried out carefully. Despite these shortcomings, GA is still one of the most widely used optimization algorithms in modern nonlinear optimization.

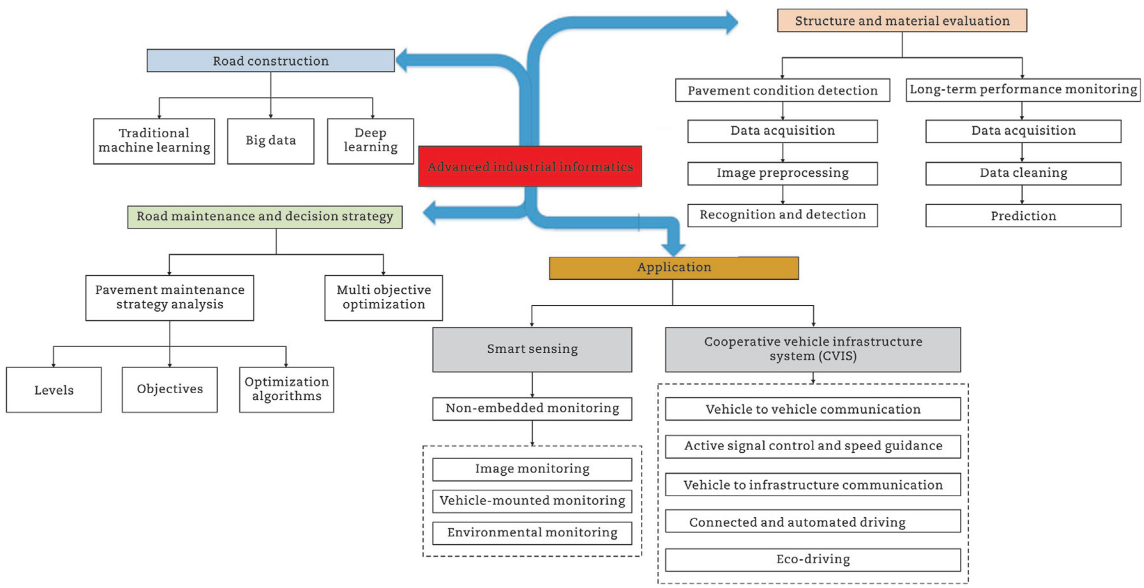

Fig. 1 – Advanced industrial informatics in modern road engineering.

In order to schedule linear construction projects, a genetic algorithm-based multi-objective optimization model was presented by Senouci and Al-Derham (2008) to schedule linear construction projects. A two-level model of a traffic network composed of some road connection categories was later developed by Król (2016). Another application of GA is Al-Hadad and Mawdesley (2010). This research presented the possibility of developing a GA-based technique model to optimize highway alignment. It put forward a new technology to optimize highway routes in three-dimensional space.

2.1.2. *Swarm intelligence*

Swarm intelligence (SI) belongs to the general field of AI, which is based on the collective behavior of elements in decentralized and self-organizing systems (Rath et al., 2020). Today, SI has great involvement in the field of the Internet of Things (IoT) and IoT-based systems to logically control their operation. SI algorithms such as ant colony optimization, artificial bee colony optimization, and social spider optimization play an important role in standardizing the process of the IoT (Rath et al., 2020).

Determining the shear strength of soil is an important work in the design stage of road construction., a hybrid AI model integrating the least squares support vector machine (LSSVM) and cuckoo search optimization (CSO) was proposed by Bui et al. (2019) to estimate this parameter of soil. The prediction accuracy of this hybrid method was better than the benchmark method including standard LSSVM, ANN, and regression tree. A reduction of the network into a much smaller complete graph and metaheuristic based on an ant colony optimization was proposed by Vodák et al. (2018). In the reference (Calis and Yuksel, 2015), ant colony optimization with parameter analysis (ACO-PA) was developed that can determine the appropriate parameter value within the predefined parameter variation range. The results showed that it can reduce transportation costs compared with the station layout generated by GA and basic ACO.

2.1.3. *Artificial neural networks*

ANN is composed of various nodes, and the function of these nodes is similar to that of genetic neurons in the human brain. It has a self-learning function and the ability to quickly find optimal solutions which can effectively deal with nonlinear problems. ANNs have recently attracted much attention because of their ability to solve the qualitative and quantitative problems and prediction tasks that appeared in the construction industry. In order to provide more accurate results with less estimation error on the estimation of expected road construction costs, with the help of the available databases, three different types of ANNs based on four indicators, namely road length, road width, planned construction duration, and planned construction cost, were formed by Tijanić et al. (2020). The proposed algorithm was proved to be used during the initial design phase when there is usually a limited or incomplete data set for the cost analysis. In another study, different ANN models were developed to estimate the cost and duration of the construction (Naik and Radhika, 2015). The application of neural networks in the formation of preliminary estimation would reduce the time and cost of data processing. It can help contractors make decisions more easily.

2.2. *Big data*

The decision-making in the early design stage of road construction has a significant impact on the road life cycle performance. In the early decision-making stage, big data technology is usually used to predict or evaluate the performance of building environments with different designs. Progress in this field can bring multiple benefits such as energy saving, waste reduction, and cost saving.

For example, the big-data-based geographic information system (GIS) technology can accurately locate the natural environment and geographic information around the construction project, so as to make the building information model (BIM) model more complete (JTTE Editorial Office et al., 2021; Liu et al., 2022; Shi and Lyu, 2021).

2.3. Deep learning

Various deep learning algorithms have been successfully applied in the field of road construction to help diagnose and standardize the causes and preventive measures, such as site planning and management, health and safety, construction cost prediction, and so on. In the reference (Shinde et al., 2020), a platform based on AI, deep learning methods, and blockchain technology was proposed. With the help of this platform, many parameters can be determined, such as how long the road construction in a specific area will be completed, how many raw materials are expected to be required, and how much labor force should be allocated. A CNN-based deep learning architecture, FrictionNet, was developed in reference (Yang et al., 2018), which can directly predict the level of pavement friction by using the texture profiles. The deep learning method needs to use a large amount of data, which means that it can continuously improve itself through more data (Lin et al., 2017). Therefore, they have become the key method of the concept of "big data", i.e., more valuable information and knowledge can be extracted from big data through deep learning technology.

However, deep learning algorithms have high requirements for data and computing power. In future work, research on model lightweight should be paid attention to for reducing the memory and speeding up the operation as much as possible. It can pave the way for the realization of the mobile terminal. In addition, it is hard to improve existing algorithms and develop new algorithms, which requires professionals and a large number of experiments. It should be noted that the "industrial" informatics discussed in this study refers to the research and applications that have been tried to be applied or at least preliminary investigated for possibility in practical engineering projects in road engineering, but not the pure "industrial" - level applications.

3. Advanced industrial informatics in road maintenance and decision strategy

3.1. Levels of pavement maintenance strategy analysis (PMSA)

Many studies have been conducted and pavement management systems have been developed for PMSA to maintain our pavement performance at a specific level with limited budgets, considering traffic, environment, and policy factors. There are three levels of PMSA including strategic, network, and project levels (Wu et al., 2012), and most studies and applications focus on the network and project levels.

The network-level PMSA includes the top-down and the bottom-up approaches. The former aimed to determine network-level maintenance strategy but cannot specify treatments for each pavement segment. The latter started by determining the optimal treatments for each pavement segment and then obtained the network-level strategy (Medury and Madanat, 2014). Lee and Madanat (2015) developed a bottom-up joint pavement maintenance optimization and used genetic algorithms (GA) to obtain the network-level maintenance strategy by minimizing the life cycle cost and maximizing the reliability of systems. Denysiuk et al. (2017) developed a bottom-up optimization that also includes two stages and employed GA to handle multiple nonlinear objectives at the network level.

The project-level PMSA is to determine the time and type of maintenance treatments. The optimal strategy can be obtained by selecting the one with the highest ratio of maintenance effectiveness over life cycle cost from all possible maintenance scenarios (Yao et al., 2019). Rashid and Tsunokawa (2012) developed a trend curve optimal control model to determine project-level PMSA considering multiple maintenance treatments. The optimal application time maximizing maintenance effectiveness (Dong et al., 2020) can be calculated based on the pavement performance models before and after treatments. However, the accuracy of the predicted parameters of post-treatment performance models is relatively low due to the high variance of the model parameters.

3.2. Objectives of PMSA

In a typical PMSA problem, multiple objectives or constraints including pavement performance, cost, environmental impacts, traffic delay time, annual or regional budget limits, maintenance activity types, policies, etc., need to be defined first. The life cycle cost analysis (LCCA) is usually adopted in the cost analysis, which aims to evaluate the cost-efficiency of maintenance strategy alternatives based on the net present value of pavement maintenance cost, agency cost, vehicle operation cost, salvage value, etc (Santos and Ferreira, 2013). The life cycle assessment (LCA) including various models of energy consumption, global warming potential, acidification potential, and respiratory effects potential, is usually adopted to evaluate the environmental impacts. After obtaining the models for calculating those objectives, the optimization algorithms which aim to find a maximum or a minimum, given a specific set of possibilities are utilized to find the optimal maintenance strategy.

With the increasing concern for sustainability, an increasing trend is to incorporate LCA in the PMSA. Usually, the marginal damage cost and environmental damage cost of pollutants and emissions are calculated as part of the cost for optimization (Huang et al., 2020; Santos et al., 2018; Yu et al., 2013; Zhang et al., 2010). However, the high uncertainties of the damage cost models cripple the effectiveness of the optimization. To overcome this limitation, genetic algorithms have been adopted to determine the optimal solutions for optimizations with more than two objectives (Yu et al., 2015).

3.3. Optimization algorithms for pavement maintenance strategy analysis

Many optimization methods in the field of operation research have been adopted for PMSA. Linear programming (LP), capable of minimizing the linear objective functions under linear inequality constraints was first adopted by Grivas et al. (1993). Integer programming (IP), which mostly refers to integer linear programming (ILP), is a type of LP whose variables are integers, and was also utilized (Wang et al., 2003). Pavement maintenance decisions span several points in time and can break apart recursively, and therefore can be solved by dynamic programming (DP), which simplifies a complicated problem by breaking it down into simpler sub-problems in a recursive manner (Ma et al., 2018).

Some researchers claimed that those traditional optimization algorithms can obtain one single optimal solution and have computing efficiency (Hankach et al., 2019; Schwefel, 2000). Updated traditional optimization algorithms are still preferred by some researchers. Medury and Madanat (2013) adopted approximate dynamic programming (ADP), which is a type of discrete-state Markov decision process-based optimization for network-level pavement maintenance strategy optimization. The ADP steps forward through time, obviating the need to loop through the entire state space in future time periods, and can overcome the dimensionality exploration associated with traditional dynamic programming methods.

3.4. Algorithms for multi-objective optimization (MOO)

Traditional optimizations are mostly single objective optimization (SOO) in which a single objective function expresses the overall performance. However, a number of factors including performance, policy, cost, environment, etc. need to be considered to decide on a pavement maintenance strategy. It is not always possible to put all objectives into one single objective function. More advanced optimization methods and algorithms are needed to solve those MOO problems. The following summarizes studies that incorporated different objectives in a single objective function to solve the MOO problems in PMSA.

3.4.1. Weighting sum method

The weighting sum method is to convert a MOO problem into a single objective optimization (SOO) problem by assigning weighting factors to the multiple objectives as shown in Eq. (1). The weighting sum method is simple, and the selection of weights depends on decision makers' preference. It has been used to assign the weights for highway safety factors based on surveys (Dissanayake et al., 1999), and to determine the maintenance needs for different components of the entire transportation infrastructure system (Sadek et al., 2003). The uncertainties of the expert's opinions can be incorporated using a fuzzy set into the weighting sum method (Tonon and Bernardini, 1999).

$$\min \sum_{i=1}^{n} \lambda_i f_i(x) \tag{1}$$

where λ_i is the weighting factor for the objective $f_i(x)$.

3.4.2. Goal programming

The goal programming is to use expected goals of objectives as constraints and to minimize the weighted sum of deviations of all objectives from their respective goals as shown in Eq. (2). Similar to the weighting sum method, goal programming uses penalty weights to reflect the relative importance and also depends on decision makers' opinions. It has been used to make maintenance decisions for bridge infrastructures (Ravirala et al., 1996), pavement networks (Wu et al., 2008), and the infrastructure including both pavements and bridges (Ravirala, 1995) to effectively incorporate multiple conflicting and prioritized objectives.

$$\min \sum_{i=1}^{n} |f_i(x) - D_i| \tag{2}$$

where D_i is the penalty weighting factor for the objective $f_i(x)$.

3.4.3. Multi-attribute utility theory

Multi-attribute utility theory (MAUT) utilizes weighting factors to convert the goal value into a utility value to build a new comprehensive single objective function. The MOO problem is then solved by maximizing the expected utility. The weights are determined by a decision-maker based on his past experiences or his own expertise. It has been used for pavement networks (Gao et al., 2012), and transportation infrastructure management including different types of highway assets such as bridges, pavements, culverts, intersections, and signs (Gharaibeh et al., 2006; Li and Sinha, 2004). The parameterized utility functions were developed to convert MOO problems into a series of SOO problems. Each parameter in the utility function serves as a weight for its corresponding objective.

3.4.4. Analytic hierarchy process (AHP)

The AHP decomposes the problem into several levels. The weight of each factor at the lowest level is obtained by pair comparison. The weight of the overall objective is obtained by analyzing and calculating from low levels to high levels. Compared with the weighting sum and goal programming methods, the AHP method helps decision-makers analyze multiple objectives more rationally by dividing the original problem into smaller problems which are easier to make decisions. The AHP (Wu et al., 2008) was adopted to build a hybrid MOO model for pavement preservation strategy analysis. Jelena et al. (2020) developed a decision support tool for maintaining damaged asphalt pavement by employing the multi-criteria preference ranking organization method for enrichment evaluation (PROMETHEE) method and the AHP method. However, it is still influenced by the intuition and preferences of the decision-makers.

3.4.5. Compromise programming

Compromise programming is to minimize the distance or the normalized deviation between solutions and the ideal solution which simultaneously optimizes each objective. In the space of the objective function, the coordinates of the ideal solution are shown in Eq. (3).

$$f(x^*) = (f_1(x^*), \cdots, f_n(x^*)) \tag{3}$$

where x^* optimizes every objective $f_i(x)$.

The compromise programming can be used for discrete variables. Fwa et al. (2000) developed a PMSA program incorporating compromise programming and GA, which can solve two- and three-objective optimizations. Xiong et al. (2012) developed a two-objective model to analyze the resource allocation problem in pavement and bridge deck maintenance. Lounis and Daigle (2013) used compromise programming for highway bridge deck maintenance by minimizing owner's costs, user costs, and environmental impacts and obtained the best trade-off between all competing objectives.

3.4.6. *ϵ-constraint method*

The ϵ-constraint method is to optimize one objective while converting other objectives into constraints to convert the MOO problem to the SOO problem. The selection of ϵ and setting the constraints are of great importance for this method. Chowdhury et al. (2000) presented a MOO based on the ϵ-constraint method to allocate highway safety resources. Chowdhury and Tan (2005) presented a constraint of multiple objective programming methods for analyzing investment decisions. Miyamoto et al. (2000) developed a new bridge management system (BMS) capable of maintenance strategy analysis by minimizing cost and maximizing quality based on a genetic algorithm and the ϵ-constraint method.

3.5. *Evolutionary optimization for multi-objective optimization*

3.5.1. *Pareto front*

The output of traditional SOO methods such as linear, nonlinear, and dynamic programming and some of the MOO algorithms which convert SOO to MOO through weighting factors obtain a single optimal solution since they are point-by-point approaches. In a MOO, there might be no single optimal solution since objective functions are often conflicting. Instead, there is a family of optimal solutions called the Pareto optimal solution set or Pareto front (PF) in the space of objective functions.

In a pool of solutions, as shown in Fig. 2, the PF is the solution in which one of the objectives cannot be improved without worsening another objective. It is a set of solutions that are non-dominated by each other but are superior to the rest of the solutions in the search space. PF rank can be used to measure solution fitness. Solutions in the PF are in Rank 1. After removing the PF, the solutions in the new front would be in Rank 2. This process will continue until the whole population is ranked.

A PF curve can be obtained by optimization algorithms such as evolutionary optimizations (EO) which are nature-inspired algorithms simulating the biological processes of natural selection, evolution, and mutation. The EO is initialized with a population of random solutions to find the optimal solution by updating generations. In the EO, PF is approximated with a set of solutions with good convergence and diversity. The following discusses the recent applications of EO algorithms in PMSA.

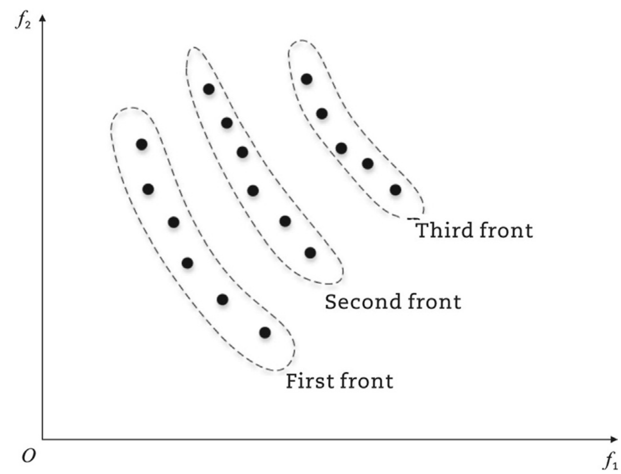

Fig. 2 – PF sorting.

3.5.2. *Genetic algorithm (GA)*

As summarized in Table 1, GA is the most widely used EO in PMSA. Many studies (Sindi and Agbelie, 2020) claimed that GA was more accurate and consistent than traditional SOO. However, some researchers (Schwefel, 2000) claimed that GA should not be used if the problem can be simplified and solved by a traditional mathematical optimization, which usually needs less time and provides better solutions. The GA algorithm cannot guarantee optimal solution for complicated constraints and usually need a large number of iterations.

3.5.3. *Non-dominated sorting genetic algorithm II (NSGA-II)*

NSGA-II is capable of finding a better spread of solutions and better convergence near the true Pareto-optimal front compared to the Pareto-archived evolution strategy. The NSGA II has been used to optimize the roadway lighting project by maximizing the average lighting level and lighting uniformity, minimizing the glare to road users, and the cost of operating the lighting system (Hyari et al., 2016). Bai et al. (2012) adopted an extreme points NSGA II for transportation asset management, considering five objectives: minimizing average pavement roughness, maximizing the percentage of bridge condition, maximizing average remaining service life, minimizing average crash rate, and maximizing average travel speed. It was found that the improved NSGA-II demonstrates a faster convergence speed and yields a better distribution than the NSGA-II. Cao et al. (2020) adopted the NSGA-II to build a three-objective pavement maintenance optimization by maximizing the average close proximity (CPX) level reduction, minimizing the maintenance costs, and minimizing the greenhouse gas emissions generated from the maintenance activities.

3.5.4. *Ant colony optimization (ACO)*

The ACO is a type of swarm intelligence (SI) which is a computational intelligence technique involving the collective study of the individual behavior of the population interacting with one another locally. In the ACO algorithm, the artificial

Table 1 – Typical applications of GA in PMSA.

Literature	Algorithm	Objective
Fwa et al. (2000)	GA	Minimize total maintenance cost, maximize maintenance work production, and maximize network pavement condition
Cheu et al. (2004)	GA	Minimize the increases in travel times in the road network for maintenance scheduling
Deshpande et al. (2010)	GA	Minimize cost and maximize pavement reliability
Jorge and Ferreira (2012)	GA/GENEPAV-HDM4	Minimize the total cost including construction, maintenance, user costs and residual values with the constraints of minimum quality, maximum budget and maintenance times
Mathew and Isaac (2014)	GA	Minimize the cost and maximize the performance
Santos et al. (2019)	Adaptive hybrid genetic algorithm (AHGA)	Minimize maintenance costs, while satisfying several technical quality standards and budgetary requirements
Elhadidy et al. (2000)	GA	Minimize maintenance cost and maximize pavement condition
Ansarilari and Golroo (2020)	GA	Minimize maintenance cost and maximize pavement performance for airport pavement maintenance strategy

ants or simulation agents locate optimal solutions by moving through a parameter space representing all possible solutions and recording their positions and the quality of their solutions. In later iterations, the artificial ants select the solution based on the heuristic value such as the objective function value. Terzi and Serin (2014) adopted the ACO to network-level PMSA considering the availability of budget, manpower, equipment, and materials.

3.5.5. *Particle swarm optimization (PSO)*

The PSO is also a SI optimization algorithm, in every iteration, each particle is updated by the two “best” values, namely “pbest” and “gbest”. Ahmed et al. (2019) utilized the PSO for PMSA which can find the optimal solution quickly and more efficiently than other optimization algorithms. Tayebi et al. (2014) compared the GA and PSO with the same case study and concluded that the PSO is easier to use and operates faster and more accurately than GA.

3.5.6. *Coyote optimization algorithm (COA)*

The COA is a newly developed metaheuristic algorithm or SI algorithm proposed by Pierezan and Coelho (2018) and Pierezan et al. (2019). In the COA, solution vectors or the artificial coyotes are randomly classified into different herds or groups and the fitness value of all coyotes is calculated. The most valuable solution in each group is the alpha. All coyotes are influenced by their groupmates and their group's alpha. The transfer culture operator produces new coyotes and resembles the mutation in GA (Qais et al., 2019). The death and birth operator removes the weakest coyotes and generates new solution vectors. Naseri et al. (2021) adopted the COA to determine long-term pavement maintenance selection strategies considering pavement roughness, budgets, CO_2 emission, etc.

4. Advanced industrial informatics in evaluations of road structure and material

During the regular services of roads, distresses will inevitably appear. Timely detection and maintenance can ensure people's travel safety while prolonging the road service life. Advanced industrial informatics has been used in the automatic identification of distresses (especially cracks), as well as the prediction of service conditions on the road surface.

4.1. *Road condition detection and evaluation*

Most of the current research on road condition detections was based on image processing technologies and machine learning algorithms, which were mainly composed of three stages: data acquisition and pre-processing, target recognition and detection, and pavement condition evaluation. The general process is shown in Fig. 3. At present, image data used in road research is usually obtained by manual photography, vehicle camera, ground penetrating radar, and other equipment (Jung et al., 2019; Li et al., 2021; Miao et al., 2014; Zhu et al., 2021).

4.1.1. *Image pre-processing technologies*

In the process of data collection and transmission, road images will be affected by different factors including noise. Meanwhile, weather, environment, and other external factors would affect the quality of the image (Ai et al., 2018). Therefore, image pre-processing is usually of great significance before the regular processing of road images.

Considering the differences in the pixel values between distresses and the unbroken matrix, image processing techniques including binarization, threshold segmentation, histogram equalization, filtering, and edge detection were used (Omanovic et al., 2013; Song et al., 2014; Zhang et al., 2020). Oliveira and Correia (2009) pre-processed images with morphological filters and dynamic thresholds to identify dark pixels corresponding to cracks. The difficulty of the thresholding technique lies in finding the appropriate feature threshold to separate the target object from the background pixel. Gao et al. (2018) performed gamma correction on the input image and expanded the details of the dark light to enhance the crack features. Then, Gaussian filtering was used to suppress and prevent the interference of Gaussian noise. Improper setting of filter window size may distort the image, resulting in the loss of valid information. Acharjee et al. (2020) used contour detection and a Canny edge filter to identify pavement potholes from video input streams. However, its correctness was easily

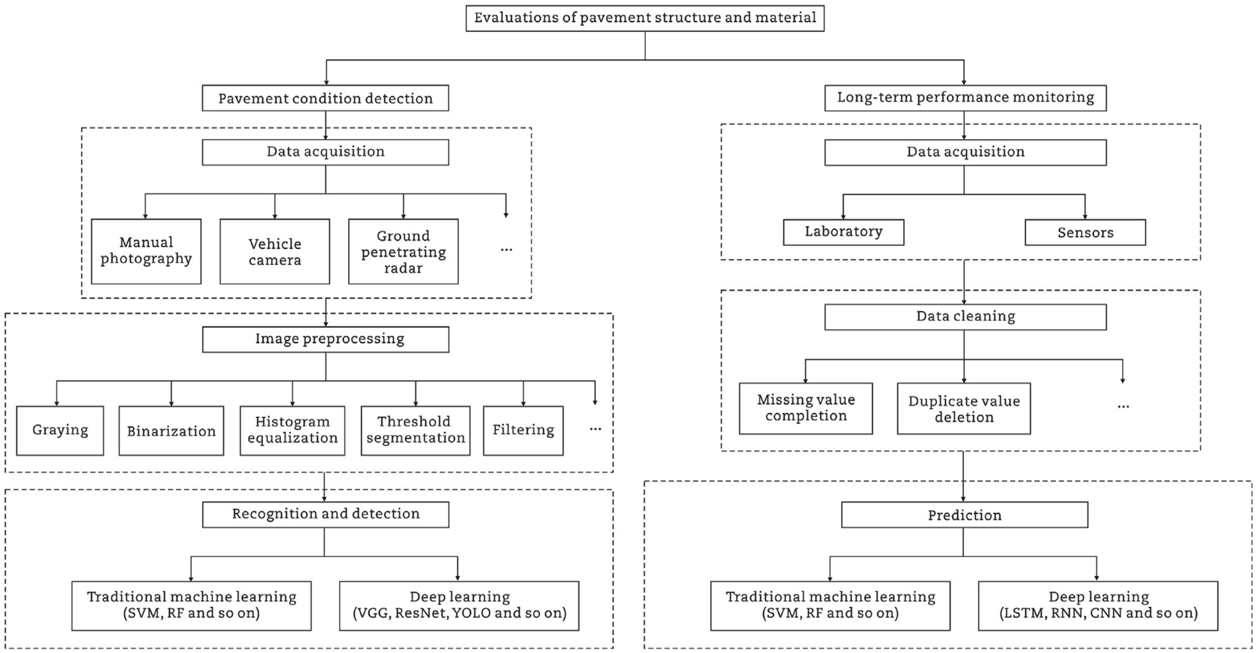

Fig. 3 – General process of intelligent detection and monitoring in road infrastructures.

affected by the intensity of pixel value, and the shadow may be incorrectly judged as a pit. The edge detection algorithm sometimes has poor performance under the condition of noisy and weak light. These methods generally required a large number of repeated experiments. In addition, the results were directly dependent on the method and size of the data. The same methods may have different results for different test datasets. In the future, the generality of the method should be studied to decrease the complexity of feature extraction and improve efficiency.

4.1.2. *Traditional machine learning methods*

With the development of artificial intelligence technology, machine learning algorithms have been widely used in the research and industry of pavement surface condition detection. Traditional machine learning algorithms include support vector machines, random forests, artificial neural networks, and so on, which all need to be labeled or artificially marked. Hoang et al. (2018) constructed a machine-learning model based on crack feature analysis, which integrated with a support vector machine and artificial bee colony optimization algorithm to perform pavement crack classification. However, this method only focused on longitudinal, transverse, and alligator cracks, while having poor performance in thin cracks. In reference (Shi et al., 2016), scholars proposed CrackForest, a road crack detection model based on random forest, which can effectively identify arbitrary complex cracks from noise according to structured information with higher speed and accuracy. Christodoulou et al. (2018) used an artificial neural network for data mining. Then the texture segmentation was carried out through entropy texture filters according to the local changes of pixel values in images. Finally, a support vector machine was used to classify and quantify pavement anomalies. Although traditional machine learning methods can achieve ideal results, the process of feature analysis and extraction still needs manual participation. This step was complicated and time-consuming, which directly affected the recognition accuracy of the model to a large extent and has low generalization ability.

4.1.3. *Deep learning approaches*

With the increase of network depth and parameters, deep learning has been developed based on machine learning. Compared with traditional machine learning methods, it is based on a convolutional neural network (CNN) and directly takes images and other data as input. So, deep learning can realize end-to-end intelligent recognition while avoiding the complicated process of manual feature extraction. Deep learning algorithms were often used for intelligent classification of road distresses, target detection, and semantic segmentation. Fig. 4 shows the results of intelligent identification on crack images by different algorithms. Song et al. (2020) proposed CrackSeg, a pavement crack detection model based on a deep convolutional neural network, which can fully mine crack characteristics and boundary information to realize pixel-level prediction. In addition, the method introduced a multi-scale extended convolution module that can obtain better recognition ability even in complex backgrounds. Feng et al. (2020) introduced a deep convolutional neural network model that integrated a single-shot multibox detector (SSD) and U-Net to process image data of different sources and sizes. The advantage was that it overcome the problems of inaccurate location and imperfect information of the single model. Moreover, it can segment cracks while detecting them to obtain geometric parameters. Based on computer vision, a CNN model was proposed to extract the characteristics of slope

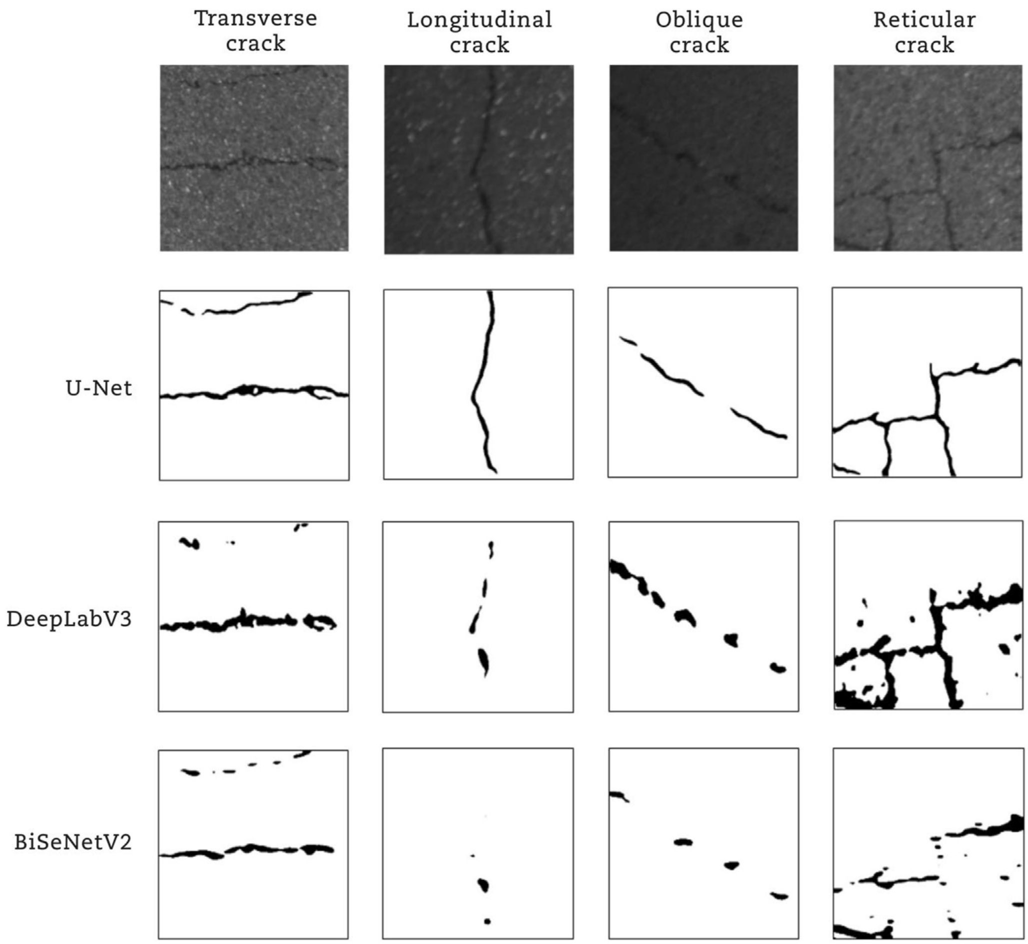

Fig. 4 – Results of intelligent identification on crack images by different algorithms.

cracks (Tian and Wang, 2021). The segmentation effect of the FSNet model designed was close to the fracture shape, and the overall identification accuracy was good. However, the recognition ability in the case of too strong or too weak image light was deficient. In addition to surface distresses, the combination of deep learning and ground penetrating radar (GPR) made it possible to conduct intelligent subgrade non-destructive detection. Li et al. (2021) first proposed to employ the deep-learning model YOLO to detect concealed cracks located below the pavement surface from GPR images. The deep feature selection network was adopted to optimize the Faster R-CNN model by adding a one-to-one layer between the input layer of the deep neural network and the first hidden layer (Gao et al., 2021). It strengthened the influence of sensitive features and improved the detection accuracy of underground pipelines and uneven settlement distresses. Due to the complexity of GPR images with a lot of noise, the detection accuracy was generally not high, which still needed to be further studied.

Models based on deep learning always require a huge number of data while having many parameters to be trained. Therefore, manual labeling was costly, and training was time-consuming. In addition, it may face the problems of insufficient video memory during the training, which needs to be equipped with a high-performance computer. Unsupervised, few-shot learning and model lightweight research should be paid more attention to in the future.

4.2. *Long-term performance monitoring*

The service performance of road infrastructure and materials mainly includes mechanical properties, physical and chemical changes, physical properties, and so on. Road researchers used artificial intelligence algorithms and other advanced analysis methods to predict the mechanical properties of pavement materials. Heidaripanah et al. (2016) used a support vector machine to predict the elastic modulus of lime subgrade soil and compared the influence of support vector regression (SVR) kernels on the results, including the polynomial kernel, radial basis function, and linear check. Chen et al. (2020) established unilateral and bilateral mechanical property prediction models based on backpropagation (BP) neural networks to predict the compressive strength, splitting tensile strength, porosity, and permeability coefficient of recycled aggregate permeable concrete.

The artificial intelligence algorithm also has a good performance in the prediction of pavement service conditions. Mahmood et al. (2020) established three prediction models of flexible pavement deterioration based on the long-term pavement performance (LTPP), a historical condition database. The results showed that the model based on artificial intelligence has a higher correlation. Therefore, it was considered to have good potential in predicting pavement deterioration. In reference (Gong et al., 2018), the authors developed two deep neural networks to realize rut prediction instead of traditional methods. The results showed that the prediction performance of the two models was better than that of the multiple linear regression method.

5. Advanced industrial informatics in smart sensing for roads

With the application of smart sensing technologies, full-scale road monitoring with structural health assessment, traffic monitoring, and road safety monitoring covered can be implemented. This section focuses on the non-embedded sensors.

5.1. *Image monitoring*

In recent years, cameras, and image analysis technologies that are sensitive to the visible band have been successfully applied to monitor and detect road surface conditions. Road images contain distress information, for example, cracks, potholes, etc. can be collected by mounting cameras on vehicles and drones. Moreover, through the application of deep learning technologies in these images, the road condition information, such as the dryness, humidity, snow or icing conditions of the road surface, and distress information, such as the length and width of the cracks, can be automatically identified by the neural network (Jonsson, 2011; Omer and Fu, 2010).

5.2. *Vehicle-mounted monitoring*

Vehicle-mounted sensors, namely sensors installed on vehicles, are used to detect and evaluate the service status of the road surface, with the characteristics of fast movement and high detection efficiency. The specialized vehicle-mounted rapid detection systems including HARRIS2 in the UK, PathRunner in the US, and CiCs in China were usually equipped with a video imaging system, a surface imaging system, a laser rutting measurement system, and a light detection and ranging system (Pan et al., 2017). After capturing the image or vibration data through the systems mentioned above, the road smoothness international roughness index (IRI) value, pothole identification, obstacle identification, etc. can be analyzed and measured.

To further reduce the costs, researchers have developed a lightweight vehicle-mounted monitoring system, including RGB-D cameras, GPS, accelerometers, and data acquisition equipment (Chen et al., 2016). The current vehicle-mounted monitoring system is developing towards low cost and lightweight, but it is still necessary to consider the influence of vehicle speed, vehicle weight, vehicle suspension system, and other factors on the measurement accuracy of vehicle-mounted sensors.

5.3. *Environmental monitoring*

Road environment monitoring usually refers to using road weather information systems to collect local weather data that affect road safety such as temperature, wind speed, wind direction, precipitation, and humidity. The monitoring of temperature and humidity, mainly relies on the forecasts of the provincial meteorological bureaus and partly relies on the data based on real-time perception along the road. At regular intervals, the road weather information system automatically transmitted the data to the road management information system. Then the data were analyzed to evaluate the possible impact of future weather conditions on road operation, and correspondingly to formulate countermeasures to ensure the normality of the road (Liu et al., 2021; Zhao et al., 2015). For road noise monitoring, road noise automatic monitoring systems were established by combining road noise automatic monitoring technology, Internet of Things technology, wireless sensor network, etc. (Dobrilović et al., 2022; Marouf et al., 2020).

In the future, the non-embedded sensors technologies will continue to be integrated into smart road systems to help improve the efficiency, safety, and sustainability of transportation. Image monitoring may realize intelligent image recognition, such as detecting pavement distress and traffic accidents, and adapt to different levels of light intensity, such as night-time and heavy fog weather monitoring and identification. Vehicle-mounted monitoring systems will continue to develop in the direction of small size, low cost, and high precision. These monitoring technologies will be combined with autonomous public transportation vehicles to detect road smoothness, identify pavement distress, and obtain a vehicle and traffic information to provide data support for road maintenance decisions and intelligent traffic control.

6. Advanced industrial informatics in cooperative vehicle infrastructure system (CVIS)

With the rapid development of intelligent sensors and wireless communication technologies, human users, vehicles, and roads in traditional transportation systems can be connected and cooperate via ubiquitous communication networks in terms of various sensors, mobile networks, wireless networks, and the Internet to achieve a safe, efficient, and sustainable transportation system, which was so called CVIS. It supports space-temporal information exchange among on-board units (OBU) of vehicles, road-side units (RSU), and intelligent terminals of human users in real-time to avoid collisions and improve traffic congestion by cooperatively perception, decision, and control, is recognized as a revolution and a new generation of Intelligent transportation systems (ITS) and will promote the traditional roads to automated infrastructure systems with new infrastructures for communications and computations. CVIS emerged in the 1990s with the famous projects of vehicle information and communication system (VICS) in Japan and vehicle infrastructure integration (VII) in the USA and developed fast in European countries and other countries worldwide (European Commission Information

Society and Media, 2022; ITS Joint Program Office US Department of Transportation, 2008; Transportation Research Board, 1998; VICS Center, 2022). In China, the first national project of CVIS was launched in 2011, and their intelligent vehicle-infrastructure cooperation systems (i-VICS) (Zhang and Yao, 2015) are developed and tested based on this project. Nowadays, CVIS has been widely deployed and tested in closed testbeds or public roadways worldwide such as MCity in the USA (Scholl et al., 2006), ETPC in the Netherlands (Voronov et al., 2021), AstaZero in Sweden (Eriksson et al., 2015) and National Intelligent Connected Vehicle (Shanghai) Pilot Zone in China (Li et al., 2018).

CVIS is an integrated system of various latest technologies and devices (Zhang et al., 2021). For the implementation of CVIS, several technologies are essential and fundamental to support V2X (vehicle-to-everything communications referring to V2V for vehicle-to-vehicle, V2I for vehicle-to-infrastructure, V2P for vehicle-to-pedestrian, and V2N for vehicle-to-network communications) including multi-modal wireless communications and automatic switch, networking technology, information security, and system integration technologies. For the application of CVIS, some related technologies such as collaborative perception, high precision positioning, swarm intelligence, parallel simulation, and edge and cloud computation are required. The typical applications of CVIS include cooperatively driving assistant and collision avoidance based on V2V or V2I (Chen and Englund, 2015; Malik et al., 2021; Naja, 2013), active signal control and speed guidance via V2I, eco-driving via V2V and V2I (Chen et al., 2018; Guo et al., 2019; Sharon and Stone, 2017). Connected and automated driving is also a typical application and an important extension of CVIS (Mahmassani, 2016). With the information sharing from surrounding vehicles and roads, vehicles can travel safely, efficiently, smoothly, and energy-efficiently with few sensors and computation powers, which is considered a promising approach to realizing full self-driving.

7. Conclusions

Road engineers have carried out a lot of research to apply advanced industrial informatics for real engineering projects in order to develop smart, safe, and sustainable roads. This paper provides a state-of-the-art review of the applications in road construction, detection, monitoring and maintenance, and the following are the conclusions.

- Big data and deep learning algorithms are current research hotspots, which provide technical support for safe and smart roads. In the future, big data should be deeply mined, and algorithms need to be improved, where the combination of them should be focused on the improvements of low computation cost and high computation efficiency.
- For road structure evaluation, most of the existing research was focused on surface cracks. Although satisfactory results have been preliminarily achieved, it was time-consuming and depended on high-performance computing equipment. In future studies, more attention should be paid to other types as well as subgrade distresses. For example, engineers should pay attention to the intelligent recognition of distress based on ground penetration radar images. In addition, the algorithms of distress recognition and detection still need to be improved for higher computation accuracy and generalization ability. Moreover, lightweight networks that can be deployed at mobile terminals and unsupervised intelligent detection methods should also be taken into consideration.
- The existing road image data acquisition and processing technologies have become mature. The application of various smart sensors in roads has preliminarily realized the industry-level monitoring of road structure and material, but there are still some problems such as high cost and vulnerable consumption. It is necessary to further develop high-performance and low-cost equipment.
- The connection and cooperation of sensors, the Internet, and other advanced industrial informatics have promoted the development of road infrastructure systems in recent years. In the future, human-vehicle and vehicle-vehicle interaction may be gradually realized. It can provide technical support for fully automatic driving, and push forward to a smart, safe, and sustainable road system.
- It should be noted that the traditional understanding of sustainability refers to meeting current needs without compromising the ability of future generations to meet their own needs. In this review, we consider sustainability as a much broader concept, in which advanced informatics approaches in road engineering contribute to extending the service life of road infrastructures while mitigating the carbon footprint through efficient design, construction, maintenance, and construction.

Author contributions

H. Yao, Z. Xu, and Y. Hou designed the structure of the review, and wrote the introduction, section 4, and conclusions; D. Wang, P. Liu, and M. Oeser wrote section 2; Q. Dong wrote section 3; Z. Ye and L. Wang wrote section 5; X. Pei wrote section 6.

Conflict of interest

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

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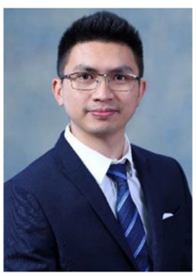

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