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Review

A Review of Deep Learning Applications in Tunneling and Underground Engineering in China

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Abstract: With the advent of the era of big data and information technology, deep learning (DL) has become a hot trend in the research field of artificial intelligence (AI). The use of deep learning methods for parameter inversion, disease identification, detection, surrounding rock classification, disaster prediction, and other tunnel engineering problems has also become a new trend in recent years, both domestically and internationally. This paper briefly introduces the development process of deep learning. By reviewing a number of published papers on the application of deep learning in tunnel engineering over the past 20 years, this paper discusses the intelligent application of deep learning algorithms in tunnel engineering, including collapse risk assessment, water inrush prediction, crack identification, structural stability evaluation, and seepage erosion in mountain tunnels, urban subway tunnels, and subsea tunnels. Finally, it explores the future challenges and development prospects of deep learning in tunnel engineering.

Keywords: deep learning; tunnel engineering; mountain tunnels; urban subway tunnels; undersea tunnels; intelligent analysis

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1. Introduction

In the 17th century, modern tunnel engineering began to rise, and the European continent started building canal tunnels [1]. By the middle of the 19th century, with the advent of the second industrial revolution, the industrial economy saw rapid development and an increasing volume of traffic, which, in turn, placed higher demands on both the quantity and quality of tunnel construction. It was not until the 1950s that people gradually mastered the basic principles of various types of tunnel construction, summarizing the design and planning methods of underground engineering; thus, tunnel engineering gradually emerged as a new research field in civil engineering. Entering the 21st century, with continuous improvement on the national economic level, China shifted its focus in tunnel construction from urban plains to hilly areas, while also strengthening the construction of high-grade highways and railroads.

By the end of 2020, the total mileage of operational tunnels in China had jumped to first place worldwide. By the end of 2022, China had put into operation a total of 42,723 tunnels, including 24,850 highway tunnels with a total length of 26,784 km, and 17,873 railroad tunnels with a total length of 21,978 km [2]; the number of cities with urban rail transit (including the "Smart Rail" system) in operation reached 58, with a total mileage of about 10,176 km, of which 26 cities have an operating mileage of more than 100 km [3]. Following the completion of cross-sea tunnels such as the Xiamen Xiang'an Undersea Tunnel, Jiaozhou Bay Undersea Tunnel, and Hong Kong-Zhuhai-Macao Bridge Undersea Immersed Tube

Tunnel, the construction of strait passages in the Bohai Strait, the Qiongzhou Strait, and the Taiwan Strait is also underway. In China's "13th Five-Year Plan", there are calls to strengthen the development and utilization of deep resources and the construction of a new pattern of underground urban space, which makes the geological conditions faced by tunnel construction more complex and further increases the construction difficulty.

In the design and construction process of tunnel engineering, the geotechnical body, situated within the complex environments of engineering geology and hydrogeology, serves as the main research object. These environments are characterized by strong non-uniformity, non-determinism, and discontinuity. The excavation of the geotechnical body and its interaction with the surrounding geological environment, along with the excavation machinery, make the tunnel excavation process a dynamically changing one in both time and space [4]. At the same time, the adverse factors affecting tunnel construction are multi-scale and multi-level. The inherent complexity of the geotechnical body makes it challenging for researchers to directly determine these factors by monitoring data in an objective manner. Previously, predictions of these factors primarily relied on the expertise of field professionals and their engineering experience, without in-depth analysis. Therefore, accurately predicting and forecasting the stability of the construction process through simulation and analysis of the mechanical behaviors and phenomena during the excavation process has become a key research topic for many scholars [5–8].

With the rapid development of computer technology, researchers have begun leveraging the powerful analytical capabilities of computers and artificial intelligence technology, combined with the fundamental theories of tunnel engineering, for the identification, study, and intelligent analysis of the mechanical behavior of rock bodies during excavation. Among these technologies, deep learning (DL), which integrates disciplines such as statistics, neuroscience, and computer science, stands out. This method, relying on data for learning and without the need for manual feature extraction, enables computers to build models that simulate human brain functions for information learning and processing. The application of deep learning in civil engineering began to expand gradually after Ian Flood first utilized the neural network method to address construction process issues in the late 1980s [9,10]. Ghaboussi was the first to apply neural network research to the ontological model of geotechnical materials. In the domestic civil engineering community, Shi et al. [11] were among the early researchers engaged in neural network studies, using artificial neural networks to analyze the relationship between the central intensity of earthquakes and their corresponding magnitudes, and addressing the issue of sample non-convergence with a filtering method. However, in actual tunnel engineering problem analyses, despite more advanced data acquisition methods and limitations imposed by the engineering environment, the feature information of the excavation face or the deformation data of the supporting structure are not effectively utilized [12], and the majority of data end up archived after project completion [13], rendering them insufficient for the full utilization of deep learning methods for analysis. Current research indicates that data mining is the primary means of addressing such issues, with many scholars already employing this technology for research on engineering problems like geologic disaster prevention and control [14], geologic advance prediction [15], and structural deformation prediction [16]. With ongoing innovations in computer technology and continuous advancements in deep learning theory, the deep learning method based on large data samples holds broad research and application prospects in tunnel engineering.

In addition, artificial intelligence and a series of intelligent products differ from the human brain in their inability to produce abstract or image thinking similar to that of the human brain. They also lack the cognitive process of understanding things inherent to the human brain. This cognitive process often stems from common sense, which includes both physical common sense and the common sense used in daily life. On the other hand, the thinking process of artificial intelligence is derived from its technological basis, namely, the chip. However, when the available data are insufficient or inaccurate, this can lead to issues in the computational processes of these products. Yet, true intelligent analysis involves understanding the essence of the subject matter from a limited amount of data. The ability to change one's thinking plays a crucial role here, leveraging the advantages of human brain thinking, including abstract and image thinking, to move from understanding the essence of things to establishing intelligent thought processes and ultimately arriving at the final analysis results.

Through the China National Knowledge Infrastructure (CNKI) and Web of Science, among other literature search engines, a total of 1068 Chinese and English articles published over the past 20 years on the topics of "deep learning", "neural network", and "tunnel engineering" were selectively reviewed. The applications of deep learning methods in tunnel engineering research areas have been categorized into 10 themes, as depicted in Figure 1. It is observed that the most extensive research has been conducted in the area of "tunnel disease identification and assessment". This primarily includes the identification of lining cracks and water leakage areas [17,18], the prediction of rockburst and collapse risk [19,20], and the control of surrounding rock deformation [21], among other factors. Feng et al. [22] combined the mean impact value algorithm (MIV-A) with the improved firefly algorithm to optimize the probabilistic neural network (PNN), using cumulative microseismic event numbers, microseismic energy, etc., as input parameters and the rockburst intensity level as the output parameter. They proposed a rockburst prediction method based on microseismic monitoring and an optimized probabilistic model, demonstrating that the prediction rate of rockburst based on this method can reach 86.75%. Cao et al. [23] integrated the empirical modal decomposition method with long short-term memory (LSTM) [24] to create a deep learning model capable of adaptively processing noisy data. This model uses the empirical modal decomposition method to break down short-term original tunnel deformation data into multidimensional data, which are then predicted by the LSTM neural network, significantly enhancing the accuracy of time series predictions.

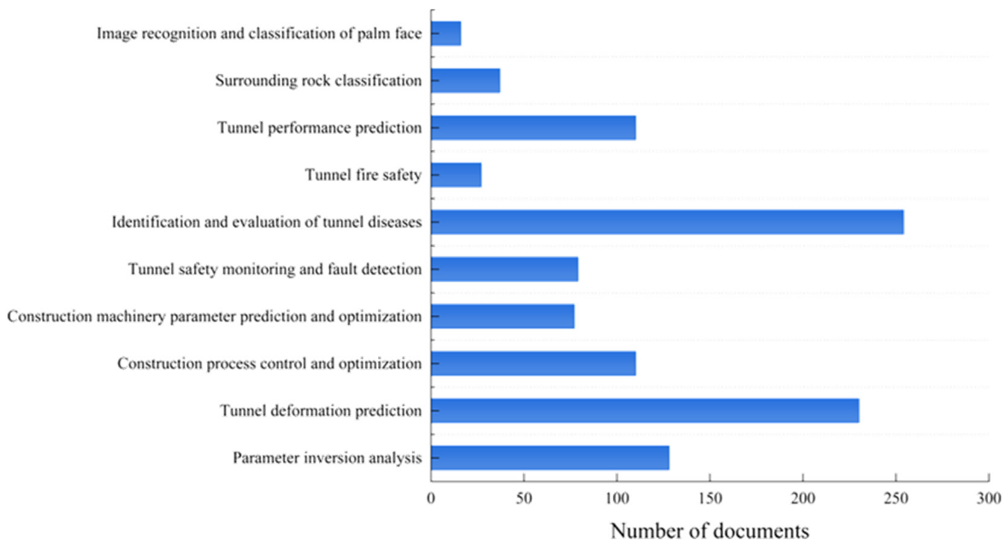

Figure 1. Main research fields of DL in tunnel engineering.

The main journals publishing research on the application of deep learning in tunnel engineering were identified, as shown in Figure 2. Notably, the English journal *Tunnelling and Underground Space Technology* has the highest number of publications in this field, totaling 67 articles. Both the Chinese journal *Chinese Journal of Rock Mechanics and Engineering* and the English journal *Applied Science Basel* have published 47 papers in this domain, ranking them second.

However, the current research on DL in tunneling engineering is predominantly focused on specific directions, with only a few overview articles analyzing DL methods within this engineering field. To address this issue, this article outlines the development of DL by reviewing articles published both in China and internationally over the past ten years.

It briefly introduces the neural network structures primarily used in DL and categorizes tunnel engineering challenges into mountain, urban, and subsea tunnel issues based on their locations. Furthermore, it discusses and summarizes the intelligent applications of the DL method across various tunnel engineering projects, along with the existing research gaps. Finally, it explores the future development directions and challenges for DL in the tunnel engineering field. To better illustrate the research ideas and content of this paper, the structure flow chart is presented in Figure 3.

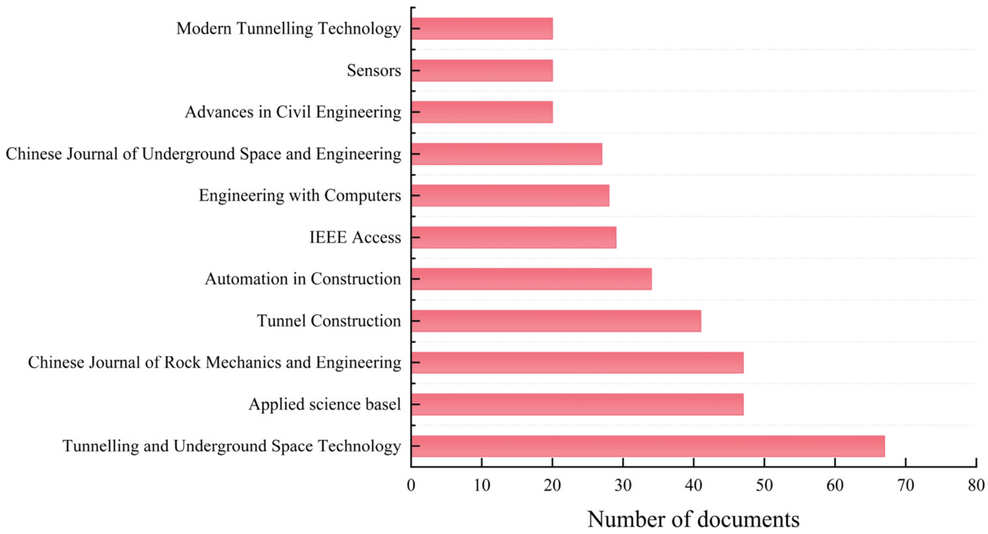

Figure 2. Published major journals on the application of deep learning in tunnel engineering.

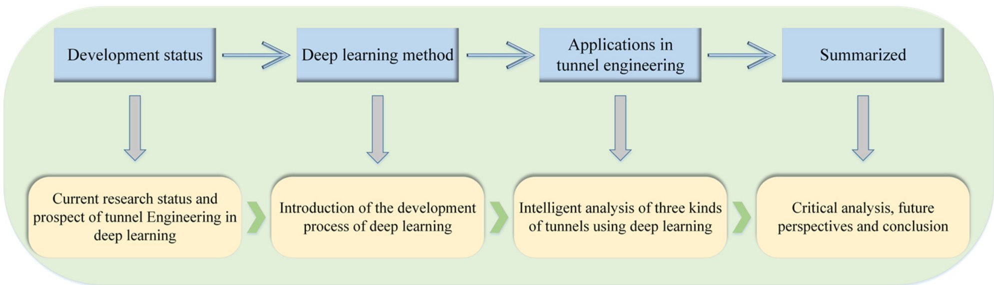

Figure 3. Research frame of DL in tunnel engineering.

2. Deep Learning Algorithm Evolution

In 2006, Geoffrey Everest Hinton, known as the "Pioneer of Deep Learning", published an article in the top academic journal *Science* with his students [25], which once again opened a wave of DL in academia and industry. As a new branch of ML, DL would go on to be widely used in driverless technology [26], natural language processing [27], speech recognition [28], medical diagnosis [29], astronomy [30], and many other fields in the following years.

DL can be viewed as a neural network containing multiple hidden layers, and its origin can be traced back to the birth of artificial intelligence (AI), i.e., as early as the 1950s. In the 1980s, a new approach based on brain-based computing proved feasible, laying the foundation for the development of DL. With the advent of the 21st century, with the speed of computer operation becoming fast enough and the computational ability becoming better, coupled with the abundance of means to obtain data at construction sites and innovation in monitoring and measurement technologies, more available data could emerge. Compared with the traditional shallow machine learning (ML) methods, DL can better overcome the problems concerning the reduced computational power and flexibility of models due to the dramatic increase in data volume.

Computers have faster and more precise computing and learning abilities than humans, while humans have a more comprehensive range of self-learning, thinking, and judging capabilities. The birth of the discipline of AI has given computers the ability to understand and think logically as humans so that computers might attain the judgment and processing of high-level semantics and even emotions. Among the many algorithms for realizing AI, ML is one of the more rapidly developing ones. Its core idea is to let the machine actively and continuously learn from a large amount of data, find the corresponding information law, and use the law to make predictions on unknown data.

As a branch of ML, DL is rooted in mathematics, computer science, and biological neuroscience. Its essence is to explore specific features of brain structure and the general principles of brain function, aiming to establish a process of continuously extracting data characteristics and to achieve the recognition ability necessary to imitate the brain with respect to images, sounds, and texts. Compared with the previous neural networks, the network structure of DL is more straightforward, and the network level is more profound, which can achieve the approximation of complex functions. Specifically, AI, ML, and DL have an inclusive relationship, as shown in Figure 4.

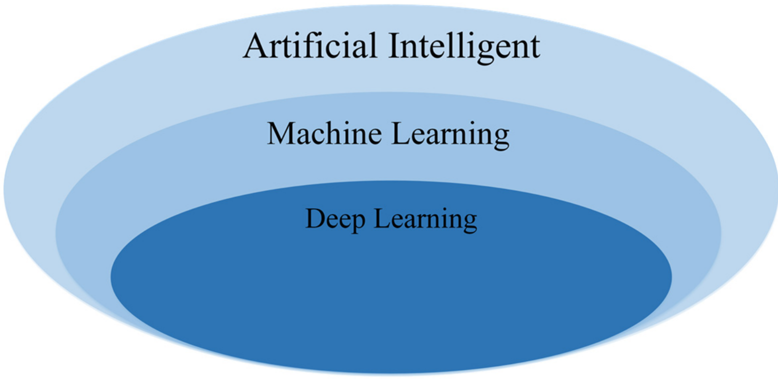

Figure 4. The relationships among AI, ML, and DL.

In a strict sense, the emergence of DL is due to the development of neural networks, while the research boom in neural networks arises through perceptrons. In the research process of DL, it would be absurd to leave the neural network alone. Since the 1940s, the establishment of theoretical neurology has made people focus on the thinking mechanism of the human brain and analyze the working principle of human neurons [31–33]. At this time, the concept of a neural network was proposed [34]. After nearly a century of tortuous development, the theory of DL has been thoroughly refined from a single-neuron model to a multi-layer deep network structure [35], from solving simple linear problems to realizing complex function approximation [36], and from shallow learning to deep learning [37,38]. Its development process can be divided into three parts according to the research process of neural networks. Figure 5 shows the main development process of DL.

There are hundreds of trillions of neurons in the human brain, granting the human brain a very high network dimension and a rich hierarchical structure. Inspired by this structure, scholars in the field of neuroscience began to use anatomical knowledge to discover the way in which the brain obtains information. With the continuous improvement of technology, researchers have discovered that the brain does not discriminate between objects directly based on the projection of the external environment on the retina; it decomposes the received signals through the multiple visual laminar structures and gradually extracts the features of objects to achieve the recognition effect [39]. As to the deep learning algorithm, it is used to simplify the complex network structure, to delete the perceptrons with a low contribution rate to subsequent learning layer by layer, and to retain the data information useful for learning.

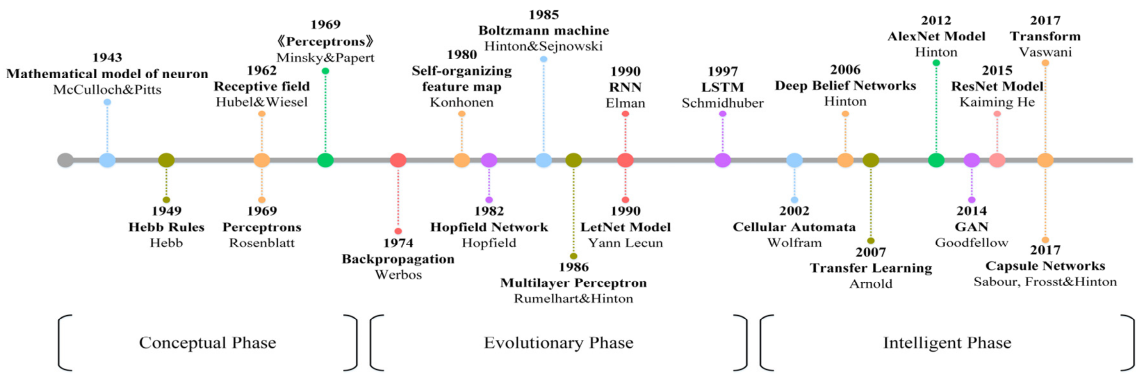

Figure 5. The development process of DL [24,31,33–35,37,40].

In 2006, Hinton published a paper on deep belief networks (DBN) in *Science*. The greedy layer-wise unsupervised learning algorithm proposed in this network solves the problem of "gradient explosion" due to the increase in the number of hidden layers in the BP algorithm. The optimization problem of the deep network structure has made breakthrough progress, and the neural network structure has completed the transformation from shallow-layer to multi-layer depth. In 2012, Hinton and his student Alex Krizhevsky et al. optimized and improved the DBN network to build the AlexNet model [41], and this model was used to win the ImageNet image recognition competition held that year with an error rate of 15%. DL has set off a broader research boom in the world, so this year is known as the "First Year of Deep Learning". In the following years, more network structures such as transfer learning [42], generative adversarial network (GAN) [40], and ResNet residual network [43] have been proposed and used in more fields. So far, the development of DL has officially entered the intelligence era, and the wave of DL based on "Big Data and Deep Model" has come.

3. Intelligent Application of Deep Learning in Tunnel Engineering

3.1. Mountain Tunnel

In 1979, the total length of mountain road tunnels in China was merely 52 km. Entering the 21st century, this figure surpassed the 1000 km mark. By the end of 2022, China had constructed 24,850 mountain tunnels, totaling 26,784 km in length. The emergence of a large number of tunnel projects has led to "multiplicity" and "length" becoming the defining characteristics of mountain tunnel construction in this century [44]. Drawing on structural reliability theory, the main areas of research have focused on the stability and durability of tunnel engineering, alongside a trend towards more mechanized construction methods for mountain tunnels. Many scholars have investigated intelligent analysis methods for addressing various problems in tunnel engineering, primarily divided into (1) intelligent analysis methods that combine numerical simulation with deep learning (DL); (2) methods that integrate numerical simulation with machine learning (ML) optimization algorithms; and (3) approaches based on DL combined with advanced monitoring tools, such as geological forecasting. During the excavation of tunnels, the disturbance to the original stratum alters the actual rock stress, with the stress state of the surrounding rock mass in mountain tunnels experiencing significant variations.

Therefore, when studying mountain tunnel engineering problems, the change of stress with time plays a vital role in its stability. By mastering the changing trend in the stress state of rock and soil mass, it can more accurately judge the stability of structures in engineering, which is also the reason why many scholars study the stress sequence in the construction process. The construction environment of mountain tunnels is complex; is often undertaken in high ground stress and deep buried environments, resulting in many geological disasters such as rockbursts, collapse, and water and mud inrush. In the past, the prediction methods of geological disasters included numerical simulation analysis, fractal geometry, fuzzy mathematics comprehensive evaluation, extensive evaluation, etc. However, the complexity of deep rock mass and the high non-linearity between disaster mechanisms and environmental factors make it difficult for traditional methods to meet the needs of construction design. Accordingly, it is good to use intelligent analysis methods based on the deep network structure for related identification, prediction, and prevention. This subsection mainly discusses the innovation of the DL method in mountain tunnels to account for the above geological disasters.

3.1.1. Rockburst Disaster

Rockburst is one of the main geological disasters in deep-buried long tunnels, often occurring in hard rock mass under high ground stress. It is characterized by apparent randomness and suddenness [45]. Due to the brittle damage of deep surrounding rock caused by excavation, unloading, or external disturbances, the elastic strain energy accumulated in the rock body is suddenly released. This results in damaging phenomena such as blasting, spalling, and ejection of the surrounding rock. Such events often cause catastrophic damage to underground engineering construction and pose a serious threat to the safety of construction personnel. Consequently, the prediction of rockburst grade and the development of intelligent early warning systems have become worldwide challenges [46].

When the DL method is used to predict, monitor, and prevent such tragedies, it is essential to choose the neural network parameters. The ability of the parameters to intuitively reflect lithology characteristics, in situ stress, initial stress field characteristics, and the development characteristics of surrounding rock joints and fissures significantly influences the network's learning process and the model's accuracy. Chen et al. [47] selected compressive strength, tensile strength, elastic energy index, and tangential stress as discriminant indexes. They used these as input-layer neurons and included two binary neurons in the output layer to represent the classification of rockburst intensity, thereby establishing an artificial neural network model for rockburst prediction. Based on the original parameter selection, Sun [48] summarized the research results of relevant scholars on influencing factors of rockburst prediction. He added a total of nine types of correlation indicators, including point load strength (I_s), tunnel burial depth (H), and burst tendency index (W_{et}), and combined these with the improved BP neural network algorithm to evaluate the propensity of rockburst occurrence during tunnel construction. Among them, the point load strength I_s depended on the rock damage load and the distance between the loading points, while the blasting tendency index W_{et} is the rock need to reach the peak strength of the rock samples in the elastic strain energy storage energy and plastic deformation dissipation of the ability of the ratio; the value can be calculated by the rock samples of the stress–strain curve obtained. Tian et al. [49] proposed a deep neural network (DNN) rockburst prediction model (DA-DNN) based on dropout regularization and an improved Adam optimization algorithm. By analyzing rockburst examples, the maximum tangential stress of surrounding rock, uniaxial compressive strength and tensile strength, and elastic energy index of rock are also used as evaluation indexes for rockburst prediction. Throughout the analysis process, the network structure itself enables autonomous selection and screening of data, avoiding the interference caused by human participation. Therefore, the prediction model can perform a complex deep relationship learning process and handle a limited amount of data with some noise. Although the concept of these physical parameters is fuzzy, their values will be some deviation from the real parameters of rock mass. However, the significance of the parameters analysis is that they can be used to obtain computational analysis results that are consistent with the measured information. In the meantime, they provide a basis for the prediction and evaluation of projects in the later stage or under the same conditions.

At the same time, the network model used in the DL process requires a large amount of data for training and verification. Generally, the greater the number of samples, the higher the potential performance ceiling of the network model becomes. However, the harsh tunnel environment poses significant challenges to data collection and acquisition.

Therefore, employing data mining (DM) techniques can effectively address these issues, enhancing both the quality and quantity of the samples. Zhang et al. [50] applied rough set theory in data mining to establish a radial basis function neural network (GA-RBF). They successfully identified a complex non-linear mapping relationship between rockburst grade and its influencing factors. Luis et al. [51] also employed data mining techniques to assess the probability of rockburst occurrences, along with their characteristics, such as type, location, depth, width, and time delay.

In addition, combining over-the-top geological forecasting tools with deep network models (refer to Figure 6) significantly enhances the accuracy and efficiency of rockburst predictions. This method monitors the development and occurrence of rockbursts, utilizing rupture and noise waveforms from pre-processed monitoring signals as inputs to the deep neural network. This approach enables real-time detection and classification of signals, allowing for the quick identification of the source of monitoring signals. It not only forecasts geological information ahead of the tunnel face but also predicts potential disaster types, representing the most effective and accurate prediction method with superior generalization capabilities currently available. Fang et al. [52] improved upon traditional advanced geological prediction methods, which often struggle with high recognition universality at lower implementation costs and reduced construction times. By integrating neural networks with drilling test technology, they devised a novel method for the intelligent analysis and identification of geological strata. The application of this method to advanced drilling data from the Jiudingshan Tunnel on the Chu-Da Expressway significantly reduced the error rate in stratum identification. Qiu et al. [53] introduced a new rockburst prediction approach using the TSP advanced geological prediction system combined with the initial geostress field obtained through RBF inversion. They emphasized that enhancing the accuracy of advanced geological prediction and in situ stress field inversion is crucial for improving rockburst prediction precision. Furthermore, leveraging microseismic monitoring technology, Zhang [54] conducted research using a deep convolutional neural network to classify microseismic waveforms of surrounding rock, focusing on noise reduction, array optimization, source localization, microseismic prediction, and rockburst warning. Building on these research findings, he established a database for the rockburst microseismic index and designed an intelligent rockburst warning platform, achieving automated monitoring of tunnel microseismic signals.

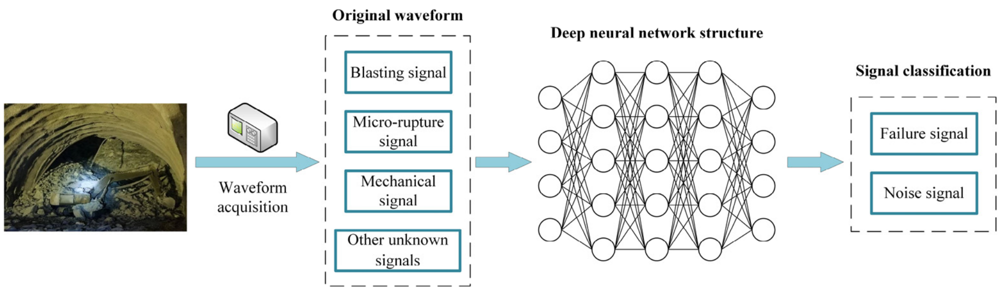

Figure 6. Schematic diagram of the process of rockburst signal recognition [54].

Based on the above analysis, it can be found that the early warning, control, and monitoring of rockburst grade for deep rock mass engineering has become an urgent problem to be solved in major engineering construction in China and even in the world. The analysis of surrounding rock stress states, realized through the seismic wave signals generated by rock microfractures and obtained by microseismic monitoring technology, has been widely used worldwide in the monitoring and prediction of rockburst disasters, achieving great success [55]. With its great advantage in data processing, the deep learning algorithm can identify the key characteristics of the monitoring data for establishing the non-linear mapping relationship between the monitoring data and the source location. Therefore, researchers tend to use the deep learning algorithm to identify effective monitoring signals from the monitoring data to predict the subsequent rockburst risk. In addition, to avoid the influence of abnormal parameter values at certain times on the prediction results, determining the evolution trend of microseismic parameters over a period is also beneficial for rockburst prediction. The prediction trend of several microseismic parameters provides a corresponding time label for rockburst prediction and risk judgment and introduces a new research idea for rockburst prediction and early warning in the field of deep underground and mine engineering.

3.1.2. Prediction of Collapse and Outburst and Water Inflow

Collapse is one of the primary risk sources in tunnel engineering, often accompanied by water and mud inrush. Figure 7a shows that the upper rock mass of the tunnel collapsed during construction, with the fallen rock mass visible at the bottom of the image. Figure 7b reveals a large amount of groundwater gushing out in the upper right corner of the excavation face. In mountain tunnels, these phenomena primarily occur in areas with unstable surrounding rock, including weathering zones, fault fracture zones, and geological structural zones. Many factors contribute to tunnel collapse, including natural factors (such as precipitation and earthquakes), geological factors (such as the grade of surrounding rock, buried depth, and groundwater content), survey and design factors (such as inaccurate geological surveys and deviations in design schemes), and construction factors (such as limited choices of excavation methods and flawed construction practices). Moreover, the relationship between the influencing factors of each disaster is complicated and ambiguous, due to the significant spatial and temporal variability of atmospheric precipitation and surface runoff. Furthermore, the complexity of the disaster mechanisms and the lack of basic information make it challenging to quantitatively assess the risks of tunnel collapse and water inrush, preventing the formation of a unified risk assessment and prediction model. Currently, the prediction methods employed for this type of disaster in China fall into three categories: (1) direct forecasting and analysis using field observation and monitoring data; (2) application of non-linear theory (including grey models, fuzzy risk assessment, and neural network models) to develop a model for predicting surrounding rock deformation; (3) prediction analysis utilizing numerical analysis methods, such as finite element, discrete element, boundary element techniques, and their combinations. Since tunnel collapse and water surge represent complex processes, often characterized by discontinuity and uneven rock deformation, a highly non-linear problem, addressing this issue poses significant challenges. Numerical analysis methods, while precise, demand stringent testing conditions and incur substantial computational costs. To mitigate these challenges, non-linear theory is integrated with existing theoretical equations. This integration serves dual purposes: it offers a theoretical foundation that enhances the accuracy and feasibility of data analysis, and it provides a methodology for rapidly assessing parameter sensitivity and for cross-verifying model results. This dual approach not only leverages the strengths of both methods but also fulfills the requirements for prediction precision and accuracy.

On the problems of the evaluation and diagnosis of collapse disaster, Chen et al. [56] summarized the factors affecting tunnel collapse according to the case data of more than 100 tunnels and established the membership function of loss and the fuzzy analytic hierarchy evaluation model of collapse risk. A comprehensive assignment method is adopted for the weight value of factors, which can satisfy both historical and practical data and reduce the possibility of interference by human factors. Wang [57] combined grey theory with cooperative non-linear theory to establish a grey-collaborative non-linear theoretical model for landslide time prediction. Chen et al. [58] took the Yinsong Water Diversion Project as an example based on the monitoring data of 18 collapse accidents during tunnel construction. The parameters such as penetration rate, rotational speed, thrust, and torque of the TBM cutter are combined into the drilling efficiency index (TPI), which was used as the input variable and output targets of DBN. This approach improves the accuracy of the algorithm while reducing the amount of data. The network structure was combined with the time series prediction method to realize the successful prediction of the unfavorable geological section of the tunnel.

(**a**) Rock mass collapse (**b**) Water inrush phenomenon

Figure 7. Tunnel vault collapse and water inrush at the tunnel face.

In the prediction of tunnel water inrush, the time series data of water inrush are normalized as the input and output variables of the model. It is a common method by which to establish a BP neural network model to predict water inrush, which has been used in the risk analysis of long-buried tunnels and karst tunnels [59,60]. Chen et al. [61] proposed an automatic detection method to quantify the water inflow on the tunnel face in view of the problems of personal subjective judgment, labor, and time consumption in the process of on-site manual monitoring of tunnel water leakage. This method utilizes the high-efficiency level of the convolution neural network (CNN) model in semantic segmentation. First, it identifies the tunnel face image samples without water inrush; then, it segments the image samples in the water inrush areas. Finally, it uses the ResNet-101 model to realize the probability classification of whether water inrush and inflow occurs in the image of the tunnel face.

Currently, there are abundant research results on the prediction of tunnel rockbursts, collapse, and water surges using deep neural networks, and relying on the powerful nolinear computational ability and learning ability of neural networks, we can realize the preliminary analysis, prediction, and forecasting of disasters in mountain tunnels under complex environmental factors. In the context of a "dual-carbon strategy", the use of deep neural networks to establish a tunnel carbon emission calculation and analysis system [62], a dynamic design and decision-making system [63], and a construction mechanization system carbon emission calculation model [64] will also become major hot directions in the future construction of mountain tunnels.

3.2. Urban Subway Tunnel

Urban rail transit is an essential infrastructure for urban construction. Rapid industrial modernization and the high concentration of the urban population led to the increasing pressure of the urban environment. A series of "urban diseases" problems, such as traffic congestion and environmental pollution, have led to the acceleration of the development of urban underground spaces. After decades of construction since the opening of the first subway in Beijing in 1969, China's urban tunnels in operation came to 1710 km in 2010, and the number of kilometers in operation grew to 4712 km by 2017. Up to 2021, 244 urban rail transit lines were opened in 45 cities across the country, and the total operating mileage increased to 7978.19 km. The construction concept behind urban underground rail is gradually changing from "social needs" to "smart city", which will alleviate the negative impacts caused by traffic pressure while expanding this concept to become an indispensable component of the future intelligent urban transportation system, improving people's living standards.

The Issue of urban subway tunnels is a crucial aspect of underground space development. Throughout the design, construction, and operation phases of urban subway tunnels, they are often subjected to various factors such as roadway traffic loads, pedestrian loads, train travel disturbances, and the loads from existing buildings above. Simultaneously, it is necessary to consider the influence of underground pipelines, underground piles, and diaphragm walls of existing buildings. These factors differentiate the structural design and construction approach of subway tunnels from that of mountain tunnels. Most subway tunnels are constructed using shield machines, and the tunnel structure mainly consists of segments. This construction method inevitably leads to issues such as cracks and water seepage during both construction and operation. However, the most significant challenge in building urban tunnels lies in controlling strata stability during excavation and managing deformation within acceptable limits for surface settlement. It is indispensable to predict the maximum surface settlement that may occur during construction and operation. In light of this context, this subsection will summarize the intelligent application of the DL (deep learning) method in addressing challenges related to recognizing shield tunnel lining defects and predicting surface subsidence values.

3.2.1. Lining Cracks and Water Leakage

Cracks in the tunnel lining will seriously affect the tunnel's stability and durability, reduce the tunnel's service life, and even more seriously, endanger the safety of trains and passengers. Therefore, it is crucial to inspect the tunnel structure in a timely manner to identify and detect the cracked lining structure. As far as subway tunnels are concerned, the shield method is often used for construction. In the process of shield machine propulsion, lining segments are assembled, and grouting is carried out outside the lining ring, reducing the impact on road traffic and nearby residents. It is precise because the tunnel lining is formed by segments, the splicing strength is low, and the cracking along the joint is easy to occur. With the aggravation of the cracking degree, the water seepage area will continue to expand, and the two often show a physical correlation.

At present, the detection methods of tunnel lining cracks and water leakage mainly adopt manual inspection methods, which use the naked eyes of inspectors to observe the tunnel surface and realize the identification work. However, due to the dark engineering environment, artificial level, and subjective judgment factors, this method will inevitably have errors, lower accuracy, and efficiency. Therefore, the rapid acquisition of tunnel lining images and the automatic identification of cracks and seepage areas based on computer vision are the new development trends in the design of detection methods.

In recent years, scholars have delved into metro tunnel lining defect detection and identification technologies based on deep learning (DL). Their research has led to the development of advanced algorithms, as illustrated in Figure 8. Xue et al. [18,65] proposed an optimized depth convolution network model V-6 based on the GoogLeNet structure. This model effectively classifies image features like water leakage, cracks, seams, and pipelines, achieving an impressive accuracy rate of 95.24%, surpassing GoogLeNet in recognition performance. To address limitations in disease location feature extraction from large-scale images, six faster R-CNN detection models were designed to detect cracks, water leakage, and other issues simultaneously. Despite some limitations due to sample size, these models show promise in improving detection outcomes. Huang et al. [66] utilized fully convolutional networks (FCN) to semantically segment images of cracks and water leakage in subway shield tunnels. Their dual-flow algorithm incorporates physical correlations between the two issues, with separate channels for crack and water leakage area segmentation. This approach outperformed shallow algorithms like the region growth and adaptive threshold methods. By employing the Mask R-CNN depth convolution network structure, researchers successfully segmented water leakage images, accurately identifying leakage traces in tunnel linings and preventing the misinterpretation of concrete spots as leaks. This method is already applicable in monitoring and identifying diseases in shield tunnel linings, showcasing the significant speed and accuracy improvements facilitated by DL methods in traditional lining defect detection.

In the early stage of disease identification and detection research, the analysis model is usually based on the edge detection algorithm, the mathematical morphology operation, and the traditional machine learning algorithm. Although it has achieved good results, its recognition process is still highly dependent on manual labeling features. It is easy to misjudge. With the continuous growth in the quantity of tunnel's under construction and the continuous accumulation of operational data, the deep learning algorithm has led to a great leap forward in development in the identification and detection of tunnel lining structural diseases because of its ability to deal with massive generalization. It shows better recognition accuracy in a tunnel environment with complex interference factors such as blind area monitoring and shadow, artificial marking, background texture, and so on. Therefore, the intelligent identification and monitoring method based on the combination of deep learning and non-destructive testing technology has become a widely used testing method in the present, and its use will in the future.

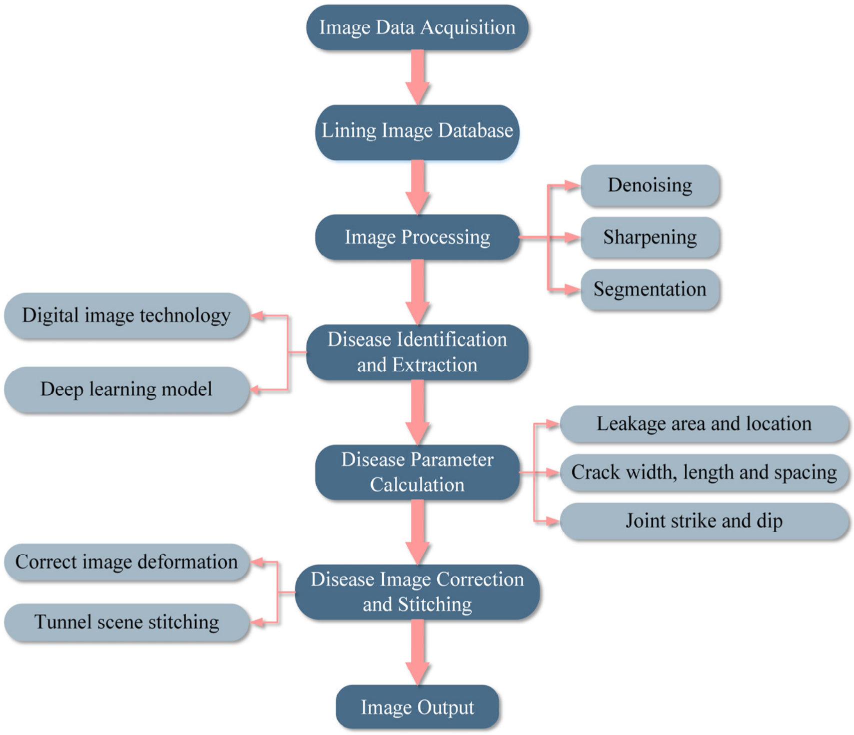

Figure 8. Algorithm flow of lining disease recognition.

3.2.2. Prediction of Settlement Value

Land subsidence in China mainly occurs in large- and medium-sized regions in the east and middle of China, especially in the Yangtze River Delta region and areas with immense groundwater exploitation. The construction process of the subway tunnel is carried out in the rock mass; the initial stress state of the original stratum will inevitably change significantly due to excavation disturbance. After the stratum stress is adjusted, its macroscopic performance is the movement and deformation of the rock mass position [67]. The ground settlement caused by subway tunnel construction gives rise to many factors, including objective factors such as the direction of surface runoff and the characteristics of excavated strata, and is closely related to subjective factors like tunnel section shape and construction technology level. Therefore, it is essential to control the tunneling speed, shield machine posture, and the grouting pressure of the shield tail in the construction process [68] to monitor the surface subsidence and the deformation of surrounding buildings.

As to the problem of predicting surface settlement values in urban tunnel construction, traditional prediction methods include empirical methods [69], theoretical methods [70], and model test methods [71], etc. However, the above methods are based only on the simplification of the tunnel structure and the construction parameters; their applicability is limited. In addition, the excavation process of tunnel-surrounding rock is a difficult self-added value system, and the above methods also struggle to achieve the real-time prediction of surface settlement and the optimization of construction machinery parameters.

With the increasing construction scale of urban subway tunnels in recent years, surface settlement prediction methods based on rock mechanics and numerical simulation have also been developed and great breakthroughs have been made. Tunnel deformation monitoring methods based on numerical simulation and tunnel stability analysis methods based on mechanical analysis and rock classification, as well as deep learning algorithms based on artificial intelligence theory, provide the theoretical basis for, and solution to, these kinds of random and fuzzy engineering problems.

The recurrent neural network (RNN) can use its recurrent hidden layer in the DL method to realize the time serialization of monitoring data and generate input data with the "memory" ability. So, the ability of the network to predict the tunnel settlement is better than that of the ML algorithms such as BP, RBF, and other algorithms. Wen et al. [72] predicted the development trend of land subsidence by using the non-linear autoregressive with eXogenous inputs neural network (NARXNN) time series prediction model with external input according to the analysis results of monitored land subsidence data. The network model takes the construction impact factor x(t) as an input unit. This impact factor combines the construction characteristics, changes in environmental conditions, and spatial and temporal effects of settlement at the measurement points. In addition, the use of input and output units with delay effects improves the accuracy and dynamic description of the prediction model, which means that the inversion results are closer to the actual situation. Li et al. [73] used stratum parameters, tunnel section parameters, and shield machine parameters as network input indicators. RNNs such as LSTM, GRU (gated recurrent unit), and traditional BP algorithms are chosen as prediction models to analyze the prediction of the maximum ground settlement caused by the subway tunnel construction. The results show that RNN models outperform the BP network model in various evaluation metrics such as root mean square error (RMSE), mean absolute error (MAE), and determination coefficient (R^2). Mahmoodzadeh et al. [74] used LSTM, deep neural network (DNN), the K-nearest neighbor algorithm (KNN), Gaussian process regression (GPR), support vector machine (SVR), DT, and linear regression (LR) based on three engineering parameters (tunnel width, tunnel depth, and construction method), and three soil parameters (elastic modulus E, friction angle, and cohesion C) were used to study the maximum land subsidence of 300 datasets of urban subway tunnels in Iran. The prediction results were analyzed via the K-fold cross-validation method, which showed that DNN, LSTM, and GPR had the best prediction results 99.37%, 98.96%, and 96%, respectively.

In addition to the RNN model, other intelligent algorithms have appeared to solve the problem of land subsidence prediction. Li et al. [75] proposed an adaptive neural fuzzy inference system (AFIFIS) to solve the problems of weak generalization ability and low correlation between parameters of intelligent algorithms such as neural networks, genetic algorithms, and grey systems. The system integrates the adaptive ability of the deep network model and the expression ability of the fuzzy system, and it comprehensively considers the relationship between the model and the key control parameters, thus providing a new solution for the rapid prediction of ground settlement during subway shield construction. Moeinossadat et al. [76] used the finite difference method to build a digital intelligent model for a section of Tehran Metro Line 7. Gene expression programming (GEP) was chosen to express the mathematical equation. The mathematical equation derived from the GEP model is written in visual basic language to estimate the land subsidence caused by tunnel construction.

Currently, urban subway tunnel construction aims for the integrated and coordinated development of underground spaces and rail transport, driven by the initial promotion of "dual-carbon strategy" and "resilient city" concepts. To construct an evaluation system for future urban metro tunnel development, it comprehensively applies non-linear theories, including deep learning, fuzzy analysis, and the analytic hierarchy process, aiming to achieve low-carbon, intelligent, and sustainable urban and rail transport development. However, existing neural network models mainly rely on monitoring data for calculations during the training process and fail to incorporate the underlying physical laws of engineering problems, leading to poor model interpretability and a lack of generalization in analysis results. Therefore, there is a need to establish a physics-informed neural network (PINN) model [77] that integrates both a physics model and a data-driven model. By deeply analyzing the relationship between data laws and physical mechanisms in conjunction with known physics mechanisms and the deep learning framework, this approach aims to facilitate applied research in complex engineering scenarios.

3.3. Subsea Tunnel

To solve the traffic problems between the straits and bays, the subsea tunnel was created under conditions without prejudice in terms of ship navigation. Different from the mountain tunnel and the urban subway tunnel. The subsea tunnels are less susceptible to the effects of weather and climate change and have a more stable and smooth passage. It is easy to connect with traffic at both ends to form a road network. Currently, there are four ways to build subsea tunnels in the world, as shown in Table 1.

Table 1. Methods of harbor tunnel construction.

Construction Method	Application of Tunnel
Drilling and blasting method; buried excavation construction	Xiamen Xiang'an Subsea Tunnel; Qingdao Jiaozhou Bay Subsea Tunnel
Prefabricated pipe section sinking method	Seabed immersed tunnel of Hong Kong-Zhuhai-Macao Bridge
Full-section excavation method based on shield tunneling machine	The Channel Tunnel
Full-section pressurized roadheader construction method	Tokyo Bay Subsea Tunnel in Japan

However, the construction period of the subsea tunnel is long, and the pore water pressure of the overlying strata of the tunnel is significant, which reduces the arching effect of the surrounding rock. Compared with the other two types of tunnels, the construction environment is qualitatively different. So, it is impossible to obtain geological information via the general survey method. In addition, the longitudinal design section of the tunnel is V-shaped; relying on the tunnel's structure is insufficient for be natural drainage. Once the water inflow is too large, the risk of disasters in the tunnel construction process will greatly increase. During the operation of the subsea tunnel, the infinite water exerts massive pressure on the top of the tunnel, which leads to tunnel leakage becoming the most serious problem. The occurrence of lining cracks will destroy the whole tunnel structure in a short time, and it is prone to collapse water inrush and other disastrous accidents.

Because of the characteristics of the subsea tunnel and the many complex properties of rock mass, researchers need to consider different boundary conditions, load types, and material characteristics parameters when analyzing them. Therefore, the key to constructing the subsea tunnel is four-fold [78]: (1) the determination of the minimum rock cover thickness; (2) the determination of the design value of water pressure; (3) the optimization of a cross-section of lining structure; and (4) the anti-drainage plan and construction measures for unfavorable sections. Thus, in the analysis of subsea tunnels, it is most significant to determine the stability of the tunnel lining structure, the erosion problem of surrounding seawater seepage caused by excavation, and the risk prediction of water inrush.

In the past, most methods to solve this kind of problem used numerical analysis and theoretical analysis. These methods require the constant modification and fitting of parameters, which makes the construction very complicated. Compared with land tunnels, the implementation of geological exploration and monitoring control is more complex, and the accuracy of the obtained mechanical parameters is worse. Once the mechanical parameters are inaccurate, bottlenecks will appear in the calculation process. Moreover, it is harder to collect images from outside the subsea tunnel than from inside, and the accuracy of images makes them difficult to use for practical analysis. In addition, there are only a few undersea tunnels built in the world, so CNN, RNN, and other models cannot be effectively used for tunnel lining disease identification and deformation prediction. Consequently, combining the deep network optimization algorithm with numerical analysis, using intelligent parameter inversion analysis is a more effective solution.

3.3.1. Structural Stability

In 2010, Xiamen Xiang'an Subsea Tunnel was completed and opened to traffic. As the first subsea tunnel in China, many scholars took this tunnel as an example by which to study the structural stability of the tunnel by inverting the construction parameters. Zhao et al. [6] used the deformation values of the tunnel monitored on site to optimize the inversion of the equivalent modulus of elasticity of the surrounding rock and the lateral pressure coefficient. Subsequently, the numerical analysis method was used to carry out the forward calculation of the above two categories, and according to the results of the forward calculation, to feed back, check, and judge whether the initial support parameters need to be further adjusted and modified in the construction process. Finally, a scientific and reasonable evaluation of the stability of the tunnel surrounding the rock was realized.

Chen et al. [79] carried out a triaxial fluid–solid coupling experiment and a triaxial rheological coupling experiment on weathered rock samples in the field and simulated the rheological finite element model of the surrounding rock. The model takes the difference between the test values and the numerical calculation results as the objective function, and the Nelder–Mead optimization method was used to invert the rheological model parameters. According to the field displacement monitoring data, the inversion analysis of weathering through the surrounding rock via parameters such as mechanical parameters, plastic parameters, and damage parameters is carried out. Based on the fluid–solid coupling theory under rheological conditions, subroutines are compiled and embedded in ABAQUS finite element analysis software for numerical simulation calculation, which realizes the reliability prediction of the long-term stability of the tunnel considering rock rheology. Wang et al. [80] developed an intelligent back analysis program based on a differential evolution algorithm and an elastic–plastic finite element solution program; compared the accuracy of parameters such as elastic modulus E, Poisson's ratio, internal friction angle, and cohesion C under different strategies; and analyzed the evolution trend of parameters of a certain section of the Xiang'an tunnel along with evolution algebra. Lv et al. [81], who made a detailed introduction to the geological exploration, alignment selection, excavation, and support of 24 Norwegian highway undersea tunnels, such as Vardø, Nappstraumen, Oslofjord, Bømlafjord, and Eiksund, studied their risk assessment methods in depth, which served as a great help in the construction of solid undersea tunnel structures in China. Li et al. [82] proposed a risk assessment analysis and identification method for undersea tunnels. The method uses six stages of tunnel planning, feasibility study, investigation and design, bidding, construction, and operation as entry points for the analysis. It was successfully applied to the structural stability, the durability of lining structure, drainage prevention system, and risk-control measures of the fault fracture zone in the Qingdao Jiaozhou Bay subsea tunnel. Professor Chen Weizhong from Wuhan Institute of Geotechnics, Chinese Academy of Sciences, took the construction process of Wuhan Yangtze River Tunnel as the engineering background; used the tunnel tube sheet strain value, tunnel temperature, and Yangtze River water level as the input parameters; learnt the spatial correlation and temporal dependence of the structural development trend by using the autoencoder algorithm and RNN, respectively; and put forward a deep-learning model that could predict multiple coupling factors (autoencoder fused temporal–spatial–load network, ATSLN), which achieves a coupled analysis of the structural external load data and spatial–temporal correlation information and can accurately predict the trend of future structural mechanical behavior [83]. The results show that the short-term structural response characteristics, the spatial location of different sensors, the internal temperature of the tunnel, and the external water pressure are the main factors affecting the development of the structure.

At present, structural health monitoring (SHM) technology is the main means for structural stability assessment [84], but this technology started later than big data technology, and its application in various engineering fields is also more limited, and the monitoring data obtained by this technology have the characteristics of huge quantity, a wide distribution of sources, and a complex correlation between data, which make it difficult for time series models to describe the effective information in the data, and the prediction effect struggles to meet expectations. Therefore, researchers apply deep learning algorithms to SHM technology to predict the structural stability of undersea tunnels with multi-factor coupling.

3.3.2. Seawater Seepage Erosion

In seepage erosion problems in submarine tunnels, the non-linear variation of the seepage coefficient has a great influence on the stability of the seepage field [85]. In general, the water pressure is transferred to the lining structure through the surrounding rock and the grouting reinforcement ring, so the coupling effect of seepage and stress fields on the lining structure must be considered when solving the unsteady seepage problem. Wang et al. [86,87] established an elastic–plastic stress–seepage–damage coupling model for rock based on analyzing the effect of groundwater on the stability of the surrounding rock in submarine tunnels and water-rich tunnels offshore. The coupling model takes into account the seepage and stress effects caused by rock cracks and inverts the coupling parameters according to observed data such as head and displacement. The stress field, seepage field, and damage field of the rock surrounding the tunnel through the river under the subway station of Dalian Maritime University were analyzed by combining the intelligent inversion analysis method with the principle of the differential evolution algorithm.

At the same time, due to the existence of a large number of inorganic salts in seawater, the contents of chlorine salt, sulfate, and magnesium salt are much higher than those in freshwater, including the influence of chemical attack medium, the climate environment, and concrete structure factors [88]. With the passage of time, this will cause corrosion damage to the lining structure and have a great impact on the durability of the tunnel (as shown in Figure 9). Tu et al. [89] think that grouting material is an essential guarantee for the subsea tunnel to operate throughout its design service life. Sulfate erosion resistance, seawater penetration resistance, chloride ion penetration resistance, and volume stability are selected as the durability evaluation indexes of grouting material, which is evaluated via a fuzzy comprehensive evaluation method. Wang et al. [90] analyzed the durability of the subsea tunnel with respect to chloride ion diffusion, steel bar corrosion, and protective layer cracking in three stages and established a life prediction model of the subsea tunnel, which was used to predict the life of the Xiang'an subsea tunnel.

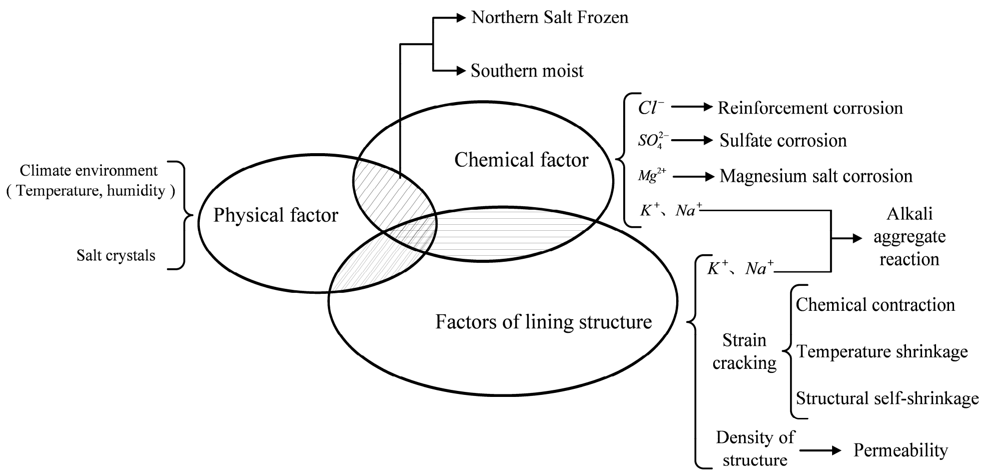

Figure 9. The construction process of the coupling degree model.

Because of the seepage problem in subsea tunnels, the finite element method combined with neural networks is still used for analysis. Due to their high risks, strong uncertainty, and the difficulties in geological survey and construction, subsea tunnels are more challenging when it comes to obtaining and calculating parameters and have higher monitoring requirements. The realization of an intelligent analysis model also requires more reliable data. In addressing the erosion problem, traditional fuzzy mathematics, risk assessment, and other methods are widely used. However, there is still a certain distance from achieving intelligent analysis. The reasons are mainly attributed to the long erosion time, the poor timeliness of data acquisition, and the low accuracy in predicting the erosion area and scope, which represent significant challenges that need to be addressed in the future.

3.3.3. Water Inrush Risk Prediction

During the process of subsea tunnel construction, there is high pore water pressure around the tunnel, which will reduce the effective stress of the surrounding rock and make the arching ability much lower than that of other kinds of tunnels. In the case of unfavorable geological sections such as fault fracture zones, the magnitude of water pressure borne by the tunnel is enough to cause geological disasters like sudden water gushing so that the overlying water on the tunnel is connected and the tunnel is submerged [91], which poses a severe threat to construction safety. Water inrush and gushing accidents not only create technical obstacles to the opening of subsea tunnels but also seriously threaten the personal safety of mechanical facilities and construction personnel. The factors leading to water inrush in the subsea tunnel are shown in Figure 10. Countries all over the world often need to consider more factors in the process of designing and building subsea tunnels. Due to the lack of dynamic analysis of groundwater seepage after tunnel excavation, the theoretical analysis method, empirical analogy method, and numerical analysis method are mainly used to predict water inrush of the subsea tunnel in China [92,93]. The former two methods can only roughly estimate the value, while the numerical analysis method is suitable for solving hydrogeological problems under complex conditions. However, the model establishment of this method generally needs to clarify hydrogeological conditions and obtain more parameters, which are usually difficult to meet in an underwater survey. If the calculation parameters are too few, the calculation results will be difficult to guarantee. Thus, this process of numerical analysis is difficult. The efficient algorithms and data analysis methods of deep learning can systematically and specifically analyze the key points and difficulties encountered in the process of sudden water disasters occurring in submarine tunnels while saving a lot of human and material resources.

Xu et al. [94] thought that the determination of the minimum overburden thickness was an important basis for the route planning of subsea tunnels, and there is a close relationship between overburden thickness and water inflow. The results of analytical and numerical analysis methods show that the relationship between water inflow and overburden thickness of subsea tunnels is approximately parabolic, and the relationship between minimum overburden thickness and seawater depth is approximately linear. Zhang et al. [95] also used this method to determine the factors the influencing water inrush and inflow of the tunnel. It is believed that the nature of the surrounding rock, the burial depth of the tunnel, and the angle of fault are related, but none of them can make a more accurate prediction result. The general empirical formula method is suitable for the subsea tunnel with a large permeability coefficient and sensitive hydraulic response. Once the surrounding environment of the tunnel changes, this method will also produce a large deviation. Li et al. [96] used the analytical method and numerical analysis method for the prediction of water inflow. On this basis, a GIS (geographic information system) is used as the basic platform by which to put the predicted results into the database of the evaluation system. Combined with the hydrogeological information during the construction process, the model parameters are continuously revised, and the final results are used as the basis for the evaluation of risk prediction problems. Xiao [97] summarized six influencing factors as the network input index of subsea tunnel water inflow according to previous work, combined it with a genetic algorithm to optimize the network, and finally achieved the prediction of water inflow work.

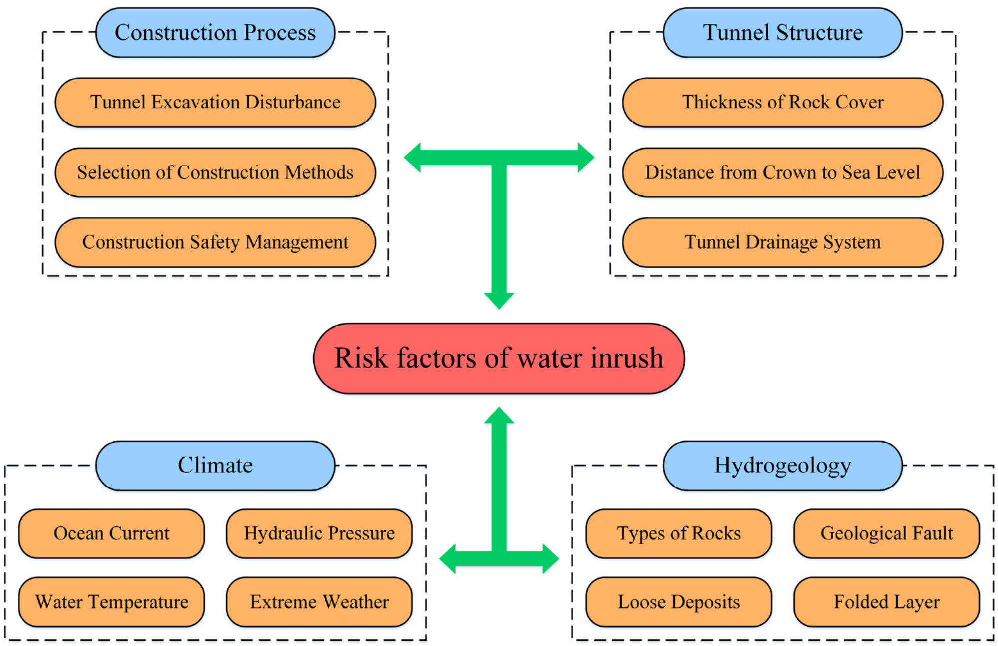

Figure 10. Diagram depicting factors causing tunnel water inrush.

The essence of sudden water disasters in submarine tunnels is the process of energy accumulation and the explosion of the underground aquifer and upper seawater pressure. Starting from the surrounding rock state of the aquifer structure and the degree of accumulation of seawater pressure, effective treatment of sudden water disasters can be realized. Restricted by the harsh underwater construction environment and high construction cost, the number of undersea tunnels in China currently under construction is relatively small, the design scheme is still being optimized continuously, and the number of training samples that can be used for deep learning algorithms is also relatively small. Hence, the existing research mainly simulates the marine environment indoors and builds a neural network model with experimental data as the sample data to realize the prediction of tunnel durability and risk assessment.

4. Problems and Prospects

Although different deep learning algorithms can be applied to the same class of problems, they are limited by the variability of the network structure itself, the principles, and the diversity of the data, which can lead to discomfort in the results. Based on the above analysis, the following problems still exist:

1. There are more factors affecting the optimization of network structure. Fully connected neural networks cannot significantly improve the accuracy of the results only by increasing the number of hidden layers; they can also produce problems such as overfitting. Secondly, although convolutional neural networks have a strong segmentation ability in image processing and recognition problems, in tunnel engineering, it is costly to obtain clear and high-quality lining structure images, and recurrent neural networks also face issues such as data loss and single data type. In addition, the training method of generative adversarial neural networks is fundamentally different from the previous networks; it requires higher computational cost and operation time.
2. The data processing process makes it difficult to achieve real-time sharing. At present, China has not established a large-scale information platform for tunnel monitoring data and geohazard information sharing, and there is a high cost of data mining, which leads to some small- and medium-sized tunnels not being able to achieve dynamic optimization of the construction process based on existing monitoring data. This increases the difficulty of the tunnel construction. In addition to the spatial and

temporal variability of geological conditions, data analysis also faces challenges in achieving correlation between the network model and numerical analysis results.

3. The accuracy of the analysis results still depends on the expert system. Although the use of deep learning methods for tunnel lining disease detection and palm face image recognition technology is relatively mature, its theoretical research is still in development. In risk assessment and performance prediction, the accuracy of the results is mostly judged by the expert system, and the research results obtained by the deep learning method still lack a certain degree of persuasiveness.

The 21st century will become the era of the high-speed, high-quality development of China's tunnels and underground spaces, and deep learning, as one of its main driving forces, will play an important role in various fields in the future. We summarize the important content of this article, draw the following schematic diagram (as shown in Figure 11), and look forward to its intelligent application in China's future tunnels and underground engineering fields in what follows.

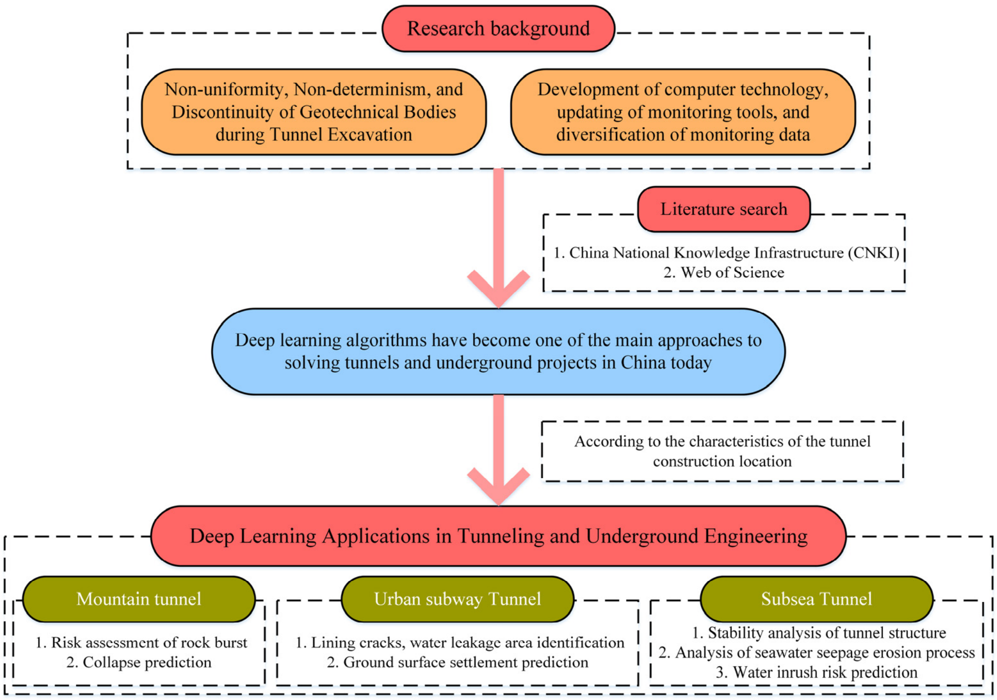

Figure 11. Summary schematic diagram of the main contents of the full text.

1. The theory of deep learning and engineering application research needs to further mature. Including the relationship between the number of samples to be trained and the calculation accuracy of the model, whether the current model can meet the engineering requirements is still the key issue to be solved. Large-scale data-mining technology is used to form a parallel integrated data-computing platform to establish a close relationship between the basic construction equipment and the intelligent platform.
2. The expansibility of the deep learning network structure should be strengthened. Most of the network structures are based on supervised learning, which is limited by the artificially labeled sample feature information in the process of use, so it is impossible to mine deeper feature information. On the other hand, the unsupervised learning network structure can extract key information from a large number of unmarked data, so this kind of network structure should be used in the intelligent analysis of tunnel engineering problems by using deep learning in the future.
3. To realize the breakthrough of tunnel construction and underground traffic design and construction technology under complex conditions, we should optimize the

construction method of mountain tunnels with high ground stress and high seismic intensity and that of undersea tunnels in deep-water, high-water-pressure environments. In the process of urban rail transit construction, it is necessary to refine the construction management system and improve the efficiency of network operation and maintenance.

4. In speeding up the exploration of intelligent diagnosis technology, rapid repair technology, and intelligent disaster prevention technology for tunnel structural diseases, the problem of aging in some tunnels in China is serious. Therefore, it is the top priority to strengthen the development and design of tunnels' full-structure risk rapid identification and assessment early warning systems, lining full-section rapid scanning and disease imaging equipment, and intelligent fire early warning technology.
5. To clarify the conception of the tunnel construction mode under the background of the "Dual-Carbon" strategy to complete the innovation of engineering technology, we should deeply integrate modern information technology with basic engineering theory, establish a new intelligent dynamic construction industry system, improve the conversion rate of scientific research achievements and practical applications, and realize cross-disciplinary and collaborative innovation in multi-disciplinary fields.

5. Conclusions

As the construction object of tunneling is a non-continuous, non-uniform geotechnical body, its mechanical properties are very complex. Moreover, in the course of tunnel construction and operation, it is difficult to rely on a single monitoring method, calculation tool, and indoor test to predict structural diseases, assess risks, and select mechanical parameters. Therefore, researchers have begun to use the monitoring of the surrounding rock displacement and stress–strain trends to deduce the nature of the geotechnical body, and they tend to utilize the rapid and accurate analysis capabilities of computers to solve the above tasks. At the same time, the rapid development of computer vision and data mining technology has solved the errors caused by the lack of tunnel monitoring data, weak disease identification technology, and strong interference of objective factors; thus, the deep learning method in the intelligent solution of tunnel engineering problems has become a new development trend. Through a brief introduction to the development of deep learning, this paper focuses on the intelligent application of the deep learning algorithm in tunnel disaster prevention and prediction problems, such as those pertaining to mountain tunnels, urban subway tunnels, and undersea tunnels. The main conclusions are as follows:

1. The development of deep learning has experienced an evolution from the conception of the network structure to the depth of network. In the progression of the big data era and the information age, the step towards the intelligent stage of the "big data + deep network structure" framework has come, and different deep network structures have gradually been put forward. However, due to the different theoretical bases and structures of all kinds of networks, there is no specific network model that can be considered the most suitable for solving all engineering problems.
2. With the development of computer vision, deep learning shines brilliantly in intelligent recognition and detection tasks such as image and voice detection, and the deep learning algorithm is used to quickly monitor and diagnose the various types of tunnel diseases. The prediction and judgment of the failure mode of the lining structure and the recognition and classification of a palm face and an image of rock are the main research directions at present. The CNN network structure has also become the most widely used deep network structure in tunnel engineering.
3. In the prediction of rockburst disasters in a mountain tunnel, our country already has certain intelligent analysis abilities, and it can use deeper neural networks to solve prediction problems such as the rockburst intensity grade, influencing factors, and so on. However, more in-depth research is needed on the prediction of the time of rockburst occurrence and the mechanism of rockbursts in different geologies, as well as collapse, water gushing, and other disasters.

4. Due to the dense population and concentrated distribution of buildings in the city, the difficulty of underground space construction is also increasing sharply with the rapid development of the city; so, the identification of tunnel lining cracks and water seepage and the prediction of surface settlement are particularly important in urban tunnel construction. The CNN is often used to identify lining diseases, while the RNN is often used to predict settlement values. The appropriate depth learning algorithm should be selected according to different working conditions and different construction methods. Random forest, support vector machine, and other machine learning methods are also good choices.
5. At present, the intelligent analysis of subsea tunnels is mainly considered from three perspectives, namely, surrounding rock stability, durability, and tunnel leakage, and the analysis method mainly depends on numerical simulation. There are few studies on the seismic analysis, internal drainage, and ventilation design of tunnels, or on the structural stability of tunnels passing through bad strata. Intelligent analysis based on deep learning methods has a long way to go in the research of subsea tunnels.

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