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A Review of Rock Damage Identification and Prediction Based on Deep Learning

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Abstract
Rock damage is a significant issue in rock mechanics and engineering, affecting properties such as strength, deformation, permeability, and fracturing. The identification and prediction of rock damage aim to understand the extent and evolution of damage and provide a basis for the design, construction, and evaluation of rock-related projects. Traditional methods for rock damage identification and prediction rely on manual observation, experimental testing, and empirical models, which have limitations such as being time-consuming, labor-intensive, subjective, and of low accuracy. In recent years, deep learning, as a powerful artificial intelligence technology, has been widely applied in the field of rock damage identification and prediction, showing superior performance and potential. Deep learning can automatically learn rock features and patterns from large amounts of data, enabling fast, accurate, and intelligent identification and prediction of rock damage. This paper reviews the research progress of rock damage identification and prediction based on deep learning, including basic concepts of deep learning, commonly used deep learning models, different types of rock damage data, methods for rock damage identification and prediction based on deep learning, challenges, and future directions. The aim is to provide a comprehensive reference and guidance for the research and application of rock damage identification and prediction.

Keywords: *Rock damage; Deep learning; Identification; Prediction; Review*

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I. INTRODUCTION

Rocks constitute a significant part of the Earth's crust and serve as the foundational material for many engineering projects. Under natural or anthropogenic influences, rocks undergo various mechanical, physical, chemical, and biological processes, resulting in different degrees of damage such as cracks, pores, spalling, and weathering [1]. Rock damage is a crucial issue in rock mechanics and engineering, affecting properties like strength, deformation, permeability, and fracturing, thereby impacting the stability, reliability, and safety of rock structures[2]. Therefore, the identification and prediction of rock damage aim to understand the extent and evolution of damage and provide a basis for the design, construction, and evaluation of rock-related projects.

1.1 TRADITIONAL METHODS

Traditional methods for rock damage identification and prediction mainly rely on manual observation, experimental testing, and empirical models [3]. Manual observation involves visually assessing the appearance and structure of rocks using tools such as the naked eye or microscope. While simple and straightforward, this method is subjective and lacks objectivity and accuracy due to human experience, skills, and subjectivity. Experimental testing involves measuring the physical, chemical, and mechanical properties of rocks using various instruments and equipment. Although this method can provide more accurate data, it requires substantial time, manpower, and resources and is challenging to adapt to complex and dynamic engineering environments. Empirical models describe and predict rock damage characteristics and patterns using mathematical formulas or charts. While providing theoretical guidance, this method relies on a large amount of experimental data and assumptions and is difficult to consider the nonlinear and heterogeneous characteristics of rocks. These methods have limitations such as being time-consuming, labor-intensive, subjective, and of low accuracy, making it difficult to meet the efficient, accurate, and intelligent requirements of rock damage identification and prediction.

1.2 DEEP LEARNING METHODS

In recent years, deep learning, as a powerful artificial intelligence technology, has been widely applied in the field of rock damage identification and prediction, demonstrating superior performance and potential [4]. Deep learning is a machine learning method based on multi-layer artificial neural networks, which can automatically learn features and patterns from large amounts of data, enabling fast, accurate, and intelligent identification and prediction of rock damage. Deep learning can handle different types of rock damage data such as images, sound waves, and microseismic data. It can utilize various deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs) to perform tasks such as classification, segmentation, detection, and generation. Compared to traditional methods, deep learning offers several advantages: (1) It does not require manual feature extraction and selection, reducing the possibility of human interference and errors. (2) It can adaptively fit the nonlinear and heterogeneous characteristics of rocks without relying on complex assumptions and conditions, improving the model's generalization ability and robustness. (3) It can achieve integrated identification and prediction of rock damage from input data to output results in an end-to-end manner, improving the efficiency and usability of the model.

This paper reviews the research progress of rock damage identification and prediction based on deep learning, including basic concepts of deep learning, commonly used deep learning models, different types of rock damage data, methods for rock damage identification and prediction based on deep learning, challenges, and future directions. The paper aims to provide a comprehensive reference and guidance for the research and application of rock damage identification and prediction. The structure of the paper is as follows: Section 2 introduces the basic concepts of deep learning and commonly used deep learning models; Section 3 introduces different types of rock damage data; Section 4 introduces rock damage identification methods based on deep learning; Section 5 introduces rock damage prediction methods based on deep learning; Section 6 discusses challenges and future directions: analyzing the challenges and limitations faced by deep learning-based rock damage identification and prediction methods, such as data quality, quantity, model complexity, and interpretability, proposing possible solutions and improvements, and envisioning future research directions and trends. The last section summarizes the main content and conclusions of the paper, addresses the research questions and objectives, indicates the significance and value of the paper, identifies shortcomings and improvements, and outlines future research directions.

II. RESULT AND DISCUSSION

The results obtained are as discussed below

2.1 BASIC CONCEPTS OF DEEP LEARNING AND COMMON MODELS

Deep learning is a machine learning method based on multi-layer artificial neural networks, which can automatically learn features and patterns from large amounts of data to perform complex tasks such as image recognition, speech recognition, and natural language processing [5]. The core of deep learning is the artificial neural network, which simulates the structure and function of human brain neurons and consists of multiple input, output, and hidden layers. Each layer consists of multiple neurons, and each neuron is connected to neurons in the previous and next layers, adjusting the transmission and processing of signals through weights and biases. The training process of deep learning involves updating weights and biases based on the loss function using the backpropagation algorithm to make the network's output as close as possible to the expected output, thereby achieving learning. The advantages of deep learning include automatically extracting high-level features from data without the need for manual feature design and selection, handling high-dimensional, nonlinear, and unstructured data, and improving model performance and accuracy. The disadvantages include the need for large amounts of data and computational resources, adjustment of multiple hyperparameters, prevention of overfitting and underfitting, and enhancement of model interpretability and credibility.

There are many types of deep learning models that can be selected based on different tasks and data. This paper mainly introduces several commonly used deep learning models:

2.1.1 Convolutional Neural Network (CNN)

CNN is a deep learning model specifically designed for processing image data, consisting of multiple convolutional layers, pooling layers, and fully connected layers. It can effectively extract local and global features of images to perform tasks such as image classification, segmentation, and detection. The core component of CNN is the convolutional layer, which applies convolution operations with multiple filters to input images, generating feature maps to extract features such as edges, textures, and shapes. The pooling layer is a downsampling layer that reduces the size and parameters of feature maps, increasing the robustness and generalization ability of the model. The fully connected layer is the output layer of CNN, flattening the output of the pooling layer into a one-dimensional vector and using multiple perceptrons to perform tasks such as image classification or regression. The advantages of CNN include effectively utilizing spatial information of images, reducing the number of parameters, and improving model performance and accuracy. The disadvantages include requiring substantial computational resources, adjustment of multiple hyperparameters, prevention of overfitting and underfitting, and enhancement of model interpretability and credibility.

2.1.2 Recurrent Neural Network (RNN)

RNN is a deep learning model specifically designed for processing sequential data, consisting of multiple recurrent units. Each recurrent unit receives input from the current time step and the previous hidden state, outputting the current output and hidden state, thereby dynamically modeling sequential data. RNN can handle sequences of different lengths such as text, speech, and video and perform tasks such as sequence classification, generation, translation, and summarization. The advantages of RNN include effectively utilizing temporal information of sequences, handling variable-length sequences, and achieving sequence-to-sequence mapping. The disadvantages include the vanishing or exploding gradient problem, difficulty in capturing long-term dependency information, difficulty in parallelizing training, and the need to enhance model interpretability and credibility.

2.1.3 Generative Adversarial Network (GAN)

GAN is a deep learning model used for generating data, consisting of two adversarial networks: a generator and a discriminator. The generator aims to generate data that is as realistic as possible, while the discriminator aims to distinguish between real and generated data. The two networks compete with each other, continually improving their capabilities until the generated data are indistinguishable from real data. GAN can generate various types of data such as images, text, and audio and perform tasks such as data augmentation, transformation, repair, and style transfer. The advantages of GAN include generating high-quality data, achieving diversified data generation, and performing unsupervised or semi-supervised learning. The disadvantages include unstable training processes, prone to mode collapse or mode missing phenomena, difficulty in evaluating the quality of generated data, and the need to enhance model interpretability and credibility.

2.2 DIFFERENT TYPES OF ROCK DAMAGE DATA

Rock damage refers to the various degrees of damage occurring in rocks due to natural or anthropogenic influences, resulting in features such as cracks, pores, spalling, and weathering. Rock damage data reflect the characteristics and patterns of rock damage, including physical, chemical, and mechanical properties of rocks, as well as their morphology, structure, and composition[6]. Rock damage data can be categorized into the following types:

2.2.1 Image Data

Image data involve capturing two-dimensional or three-dimensional images of the appearance and structure of rocks using devices such as cameras, scanners, and microscopes. They visually depict features such as color, texture, shape, cracks, and pores in rocks and serve as essential data sources for rock damage identification and prediction. The advantages of image data include easy acquisition, rich information, and suitability for deep learning-based rock damage identification and prediction methods. The disadvantages include susceptibility to factors such as lighting, angle, and resolution, requiring preprocessing and enhancement to improve the quality and usability of images.

2.2.2 Sound Wave Data

Sound wave data involve detecting sound waves emitted and received by rocks using devices such as sound wave transmitters and receivers. They can reflect properties such as density, elastic modulus, Poisson's ratio, and crack density in rocks and serve as critical data sources for rock damage identification and prediction. The advantages of sound wave data include non-destructive detection of the internal structure and damage extent of rocks, suitability for complex and dynamic engineering environments, and compatibility with deep learning-based rock damage identification and prediction methods. The disadvantages include susceptibility to noise, interference, attenuation, requiring filtering, denoising, and enhancement to improve the quality and usability of sound wave signals.

2.2.3 Microseismic Data

Microseismic data involve monitoring microseismic waves generated by rocks using microseismic instruments. They can reflect properties such as stress state, fracture process, and fracture mode in rocks and serve as essential data sources for rock damage identification and prediction. The advantages of microseismic data include real-time monitoring of rock damage evolution and failure trends, providing dynamic information about rocks, and suitability for deep learning-based rock damage identification and prediction methods. The disadvantages include susceptibility to noise, interference, localization errors, requiring denoising, clustering, and localization to improve the quality and usability of microseismic signals.

2.3 DEEP LEARNING-BASED ROCK DAMAGE RECOGNITION METHOD

Rock damage recognition refers to the process of judging and classifying the types, extent, and locations of rock damage based on rock damage data. Rock damage recognition is the foundation of rock damage identification and prediction, as well as the premise of rock damage analysis and evaluation. The deep learning-based rock damage recognition method refers to using deep learning models to extract features and classify rock damage data, thereby achieving automated and intelligent recognition of rock damage [7]. This section mainly introduces several deep learning-based rock damage recognition methods:

2.3.1 Convolutional Neural Network (CNN) Based Rock Damage Image Recognition Method

This method utilizes convolutional neural networks to extract features and classify rock damage image data, realizing rock damage image recognition. Depending on the task, different CNN architectures such as AlexNet, VGG, ResNet, as well as different loss functions and optimization algorithms like cross-entropy, mean squared error, stochastic gradient descent, can be selected to enhance the model's performance and accuracy. The advantage of this method is its effective utilization of spatial information in images, enabling the extraction of both local and global features, and facilitating tasks such as rock damage classification, segmentation, and detection. However, this method requires a large amount of annotated data, adjustment of multiple hyperparameters, prevention of overfitting and underfitting, and enhancement of model interpretability and credibility.

2.3.2 Recurrent Neural Network (RNN) Based Rock Damage Acoustic Recognition Method

This approach employs recurrent neural networks to extract features and classify rock damage acoustic data, achieving rock damage acoustic recognition. Similar to CNN-based methods, different RNN architectures such as LSTM, GRU, BiRNN, along with different loss functions and optimization algorithms, can be chosen to enhance model performance and accuracy. The advantage lies in effectively utilizing the temporal information of acoustic signals, extracting features such as frequency, amplitude, phase, and accomplishing tasks such as rock damage regression, generation, and transformation. However, challenges include gradient vanishing or exploding problems, difficulty capturing long-term dependencies, training parallelization issues, and the need to improve model interpretability and credibility.

2.3.3 Generative Adversarial Network (GAN) Based Rock Damage Image Generation Method

This technique utilizes generative adversarial networks to generate and transform rock damage image data, realizing rock damage image generation. Depending on the task, different GAN architectures such as DCGAN, WGAN, CycleGAN, as well as different loss functions and optimization algorithms like least squares, Wasserstein distance, cycle consistency, can be employed to enhance model performance and accuracy. The advantage is the ability to generate high-quality images, achieve diversified image generation, and perform unsupervised or semi-supervised learning. However, challenges include unstable training processes, occurrences of mode collapse or mode missing phenomena, difficulty in evaluating the quality of generated images, and the need to improve model interpretability and credibility.

2.4 DEEP LEARNING-BASED ROCK DAMAGE PREDICTION METHOD

Rock damage prediction refers to the process of predicting and evaluating the evolution and trend of rock damage based on rock damage data. It serves as both the purpose of rock damage identification and prediction and the result of rock damage analysis and evaluation. The deep learning-based rock damage prediction method involves using deep learning models to extract features and perform regression on rock damage data, thereby achieving automated and intelligent prediction of rock damage[8, 9]. This section mainly introduces several deep learning-based rock damage prediction methods:

2.4.1 Convolutional Neural Network (CNN) Based Rock Damage Image Prediction Method

This method utilizes convolutional neural networks to extract features and perform regression on rock damage image data, realizing rock damage image prediction. Depending on the task, different CNN architectures such as AlexNet, VGG, ResNet, as well as different loss functions and optimization algorithms like mean squared error, root mean squared error, stochastic gradient descent, can be chosen to enhance model performance and accuracy. The advantage lies in effectively utilizing spatial information in images, extracting both local and global features, and accomplishing tasks such as rock damage regression, generation, and transformation. However, similar to the recognition method, challenges include the need for a large amount of annotated data, adjustment of multiple hyperparameters, prevention of overfitting and underfitting, and enhancement of model interpretability and credibility.

2.4.2 Recurrent Neural Network (RNN) Based Rock Damage Acoustic Prediction Method

This approach employs recurrent neural networks to extract features and perform regression on rock damage acoustic data, achieving rock damage acoustic prediction. Similar to CNN-based methods, different RNN architectures such as LSTM, GRU, BiRNN, along with different loss functions and optimization algorithms, can be chosen to enhance model performance and accuracy. The advantage lies in effectively utilizing the temporal information of acoustic signals, extracting features such as frequency, amplitude, phase, and accomplishing tasks such as rock damage regression, generation, and transformation. However, challenges include gradient vanishing or exploding problems, difficulty capturing long-term dependencies, training parallelization issues, and the need to improve model interpretability and credibility.

2.4.3 Generative Adversarial Network (GAN) Based Rock Damage Microseismic Prediction Method

This technique utilizes generative adversarial networks to generate and transform rock damage microseismic data, realizing rock damage microseismic prediction. Depending on the task, different GAN architectures such as DCGAN, WGAN, CycleGAN, as well as different loss functions and optimization algorithms like least squares, Wasserstein distance, cycle consistency, can be employed to enhance model performance and accuracy. The advantage is the ability to generate high-quality microseismic signals, achieve diversified microseismic generation, and perform unsupervised or semi-supervised learning. However, challenges include unstable training processes, occurrences of mode collapse or mode missing phenomena, difficulty in evaluating the quality of generated microseismic signals, and the need to improve model interpretability and credibility.

2.5 CHALLENGES AND FUTURE DIRECTIONS

Although deep learning-based rock damage recognition and prediction methods have made some progress and achievements, they still face challenges and limitations, requiring further research and improvement. This section mainly discusses challenges and future directions in the following aspects:

2.5.1 Data Quality And Quantity

Data quality and quantity are fundamental to deep learning, directly impacting model performance and accuracy. Rock damage data are often affected by noise, interference, decay, resolution, etc., necessitating preprocessing and enhancement to improve data quality and usability. Moreover, obtaining and annotating rock damage data is often time-consuming and resource-intensive, resulting in insufficient data quantity and diversity, requiring data augmentation and expansion to improve both.

2.5.2 Model Complexity And Interpretability

Models are the core of deep learning, and their complexity and interpretability directly affect model efficiency and credibility. Rock damage models often require multi-layer artificial neural networks and numerous parameters and computations, increasing model complexity and training time and consuming substantial computational resources, thereby reducing model efficiency and usability. Additionally, rock damage models are often black boxes, making it difficult to understand and interpret the internal mechanisms and output results, thereby reducing model interpretability and credibility, necessitating improvements in transparency and auditability.

2.5.3 Model Generalization And Robustness

Model generalization and robustness are the goals of deep learning, directly influencing model adaptability and stability. Rock damage models often suffer from overfitting or underfitting, leading to insufficient model generalization and difficulty adapting to new data and environments, requiring regularization, pruning, ensemble methods, etc., to improve model generalization. Additionally, rock damage models are often susceptible to factors such as outliers, noise, attacks, etc., leading to insufficient model robustness and difficulty ensuring model stability and security, necessitating methods such as anomaly detection, denoising, defense, etc., to improve model robustness.

III. CONCLUSION

This paper reviewed the research progress of deep learning-based rock damage recognition and prediction, including basic concepts of deep learning, commonly used deep learning models, different types of rock damage data, deep learning-based rock damage recognition and prediction methods, challenges, and future directions. The main contents and conclusions of this paper are as follows:

Deep learning is a machine learning method based on multi-layer artificial neural networks, which can automatically learn features and patterns from large amounts of data, enabling complex tasks such as image recognition, speech recognition, natural language processing, etc.

There are many types of deep learning models, and different models can be selected according to different tasks and data, such as convolutional neural networks, recurrent neural networks, generative adversarial networks, each with its own advantages, disadvantages, and applicability.

Rock damage data can be divided into image data, acoustic data, and microseismic data, which can reflect characteristics such as the appearance, structure, properties, and damage of rocks, serving as important data sources for rock damage recognition and prediction.

Deep learning-based rock damage recognition and prediction methods can accomplish tasks such as classification, regression, generation, and transformation of rock damage based on different data types and model types, improving the performance and accuracy of rock damage recognition and prediction.

Although deep learning-based rock damage recognition and prediction methods have made some progress and achievements, they still face challenges and limitations, requiring further research and improvement in aspects such as data quality and quantity, model complexity and interpretability, model generalization and robustness.

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