A Survey of Machine Learning Applications in Microseismic Signal Recognition and Classification

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***Abstract*—Effective microseismic event identification and classification form the bedrock of data analysis in microseismic monitoring systems, facilitating real-time source location, rock-burst prediction, and mine safety. However, the complex mining environment necessitates preprocessing of sensor-collected microseismic signal data, plagued by noise. Traditional methods often yield inaccurate results when events exhibit similar traits. Machine learning's high precision separation proves promising, anticipating safety alerts by learning historical microseismic event patterns, and applying them to real-time data for predictive analysis. This approach mitigates inefficiencies and errors associated with manual recognition. Hence, machine learning has gained substantial traction in microseismic monitoring. This paper reviews recent machine learning applications in microseismic signal recognition and classification, addressing limitations of traditional methods, highlighting developmental disparities, presenting machine learning-based categorization, and summarizing advancements in signal recognition models. Lastly, the potential and challenges of machine learning in microseismic signal recognition are discussed.**

***Keywords*—microseismic signals; event waveforms; classification and recognition; machine learning; image recognition**

I. Introduction

In recent years, the deep integration of information technologies such as the Internet of Things, big data, and artificial intelligence with modern mining techniques and operations has propelled the evolution of smart mines from conceptualization to realization [1]. Notably, microseismic monitoring methods based on acoustic emission and seismology have emerged as pivotal components of mine safety monitoring, finding extensive utility across domains encompassing stress impact in coal mines, rockburst, mining-induced seismicity [2], slope instability [3], and other critical facets [4]. Facilitating this is the microseismic monitoring system (MMS), which includes functions such as microseismic signal acquisition, multi-channel clock synchronization, noise attenuation, automated onset detection, source localization, analysis of rock microfracture stress, and interpretation. Leveraging seismic analysis methods, allows for precise determination of seismic attributes, including time, spatial location, magnitude, frequency domain characteristics, and source mechanisms. These calculated results enable the visualization and prediction of spatiotemporal changes in microseismic event evolution, consequently enabling continuous monitoring and early-warning systems for potential disasters [5]. The MMS usually consists of sensors, data collectors, signal processors, underground data centers, and surface monitoring facilities, as illustrated in Fig.1.

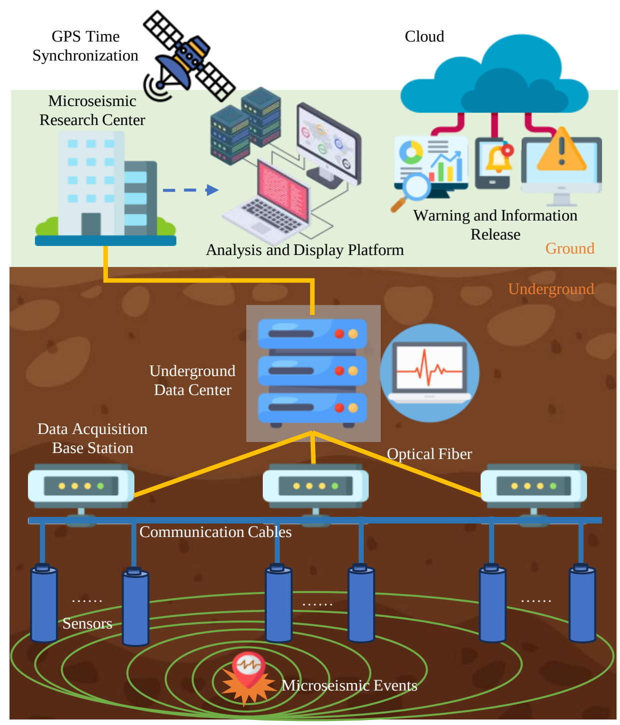

Fig. 1. The composition of a smart mine microseismic monitoring system

Due to the complex mining environment, the MMS captures a diverse range of signals from the seismic sources. A microseismic event is characterized by the generation of elastic waves that is generated when a rock breaks and is used primarily to predict earthquakes resulting from the structural instability of the rock [6]. These waves are considered valuable signals and are the primary focus of analysis in microseismic monitoring systems. Blasting is an event where rock fragmentation is induced by the shock wave from an explosive blast. Depending on the study's objective, blasting is at times treated as noise and at other times as a valuable signal. Rock drilling events involve the engineering process of drilling holes in the rock. The vibrations produced by different equipment during mining operations are detected by the MMS across a range of frequencies, becoming characteristic of disruptive noise. The data received by the signal detector varies based on the type of event triggered, and the waveforms generated from the corresponding data are depicted in Fig.2.

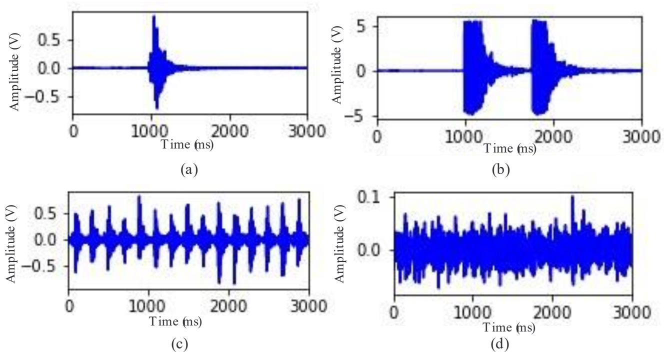

Fig. 2. Examples of waveforms for different types of events. (a) Microseismic event; (b) Blasting; (c) Drilling; (d) Noise.

Accurately identifying the types of seismic sources within the monitored area, reasonably distinguishing between different sources, and extracting valid events become the basis of research in the application of microseismic monitoring technology [7]. Despite the widespread application of MMS in rock stability analysis, extracting microseismic events directly and accurately from complex environments remains challenging, especially due to the interference of various noises and explosions. Traditional methods for identifying microseismic signals rely on manual expertise and engineering experience, leading to significant workloads, time consumption, and vulnerability to individual empirical errors. Researchers have extensively investigated methods to accurately identify microseismic signals in mining environments [8]. Recently, there has been a notable increase in the use of deep learning-based network models. These models automatically extract distinctive features from diverse waveforms, establishing an image classification framework for intelligent recognition of microseismic events. This technological approach, reinforced by machine learning and computer vision, surpasses traditional statistical methods, thereby improving the efficiency of microseismic event detection in mining operations. Consequently, mine disaster monitoring systems acquire valuable microseismic data, facilitating subsequent analyses such as source localization, magnitude prediction, and enabling timely early warnings for potential induced seismic activities.

This paper offers a review of the current research status of machine learning in microseismic signals identification. Initially, we provide a succinct overview of the evolution of traditional recognition methods and machine learning approaches, along with a brief analysis of their respective strengths and limitations. Then, we categorize machine learning methods based on their characteristics and discuss the latest research progress in microseismic event identification. Finally, the opportunities and challenges facing machine learning are explored.

II. LITERATURE REVIEW

Early microseismic signal recognition relied on manual expertise [9]. With advancements in hardware and software technology, contemporary methods for classifying microseismic signals can be grouped into three primary categories: spectral analysis, statistical analysis, and machine learning [10]. Spectral characteristics involve the analysis of dynamic signals in the frequency domain. The results of this analysis are observed as spectral curves, representing different physical quantities against frequency on the horizontal axis. Due to the demanding expertise required for spectrum analysis, its practical application in engineering presents challenges. Considering that microcracks in rocks release energy as seismic waves and blasting serves as a human-induced active source, the source parameters in these two signal types exhibit differences. Statistical methods have experienced significant growth in the early 21st century. Nonetheless, their parameter extraction and model selection continue to heavily rely on the researcher's subjective experience, which in turn affects the accuracy of the classification model. Furthermore, overlooking correlations between parameters can lead to inadequate recognition. Before constructing a classification model, it is essential to analyze each parameter, taking into account their correlations with other variables and their appropriateness for a particular model. This process unavoidably prolongs computational time [11].

A widely used approach in constructing classifier models involves extracting key parameters from the original waveform or seismic source to create an event classifier, facilitating the differentiation of various events within microseismic data. Waveform characteristics encompass the analysis of waveforms across time and amplitude domains. Parameters derived from waveform correlation usually include time and frequency variation parameters, spectral ratio, maximum frequency, P and S wave amplitude ratio [12], signal duration, first peak amplitude, and maximum peak arrival time. Characteristic parameters extracted from the seismic source frequently involve the seismic moment of the event, seismic energy, event onset time, stress drop, number of sensor triggers, and corner frequency.

Throughout the late 20th and early 21st centuries, a wide array of statistical methods have been employed in constructing classification models for microseismic events. These methods encompass regression analysis [13], discriminant analysis [14], principal component analysis (PCA) [15], and support vector machines (SVM) [16] et al. Neural networks were utilized in the analysis of geophysical signals as early as 1996, with Dowla [17] pioneering their use to tackle challenges such as seismic discrimination and event classification. Taylor [18] employed a maximum likelihood Gaussian classifier and a backpropagation (BP) neural network to perform multivariate discriminant analysis on seismic and blast events. Yang et al. [19] introduced a bio-inspired image recognition model that utilized the BP algorithm and convolutional neural network (CNN), which established the groundwork for modern computer vision.

Increasingly, the discrimination method effectively differentiated between earthquakes and blasts, yielding an identification accuracy of 95%. Orlic et al. [20] employed a specially designed genetic algorithm to autonomously search for seismic features, yielding an 85% accuracy in this classification method. Vallejos et al. [21] employed logistic regression and neural networks to classify microseismic events and explosions, both attaining classification accuracies surpassing 95% at their respective optimal decision thresholds. Dong et al. [5] used random forests (RF), SVM, and Naïve Bayes classifiers to categorize microseismic events and explosions. The results revealed that the RF model attained not only higher accuracy in automatic classification but also ordered the discriminators based on the calculated weight values. Jiang et al. [22] utilized Fast Fourier Transform (FFT) spectral analysis to distinguish between rock fracture signals and mine blast signals.

By analyzing distinct characteristics of microseismic and blast waveforms, Dong et al. [6] extracted five typical parameters along with a temporal probability density function and a probability density function of the time difference of neighboring blasts' origin. These were then employed as discriminators, and the two waveforms were classified using Fisher, Naïve Bayesian classifiers, and logistic regression. Shang et al. [23] employed PCA-based artificial neural networks (ANN) to improve the classification of microseismic events and explosions. They compared these with logistic regression, Bayes, and Fisher classifiers, demonstrating that the PCA-ANN exhibits superior performance. While being an effective classification method, its success depends on the accurate analysis and extraction of seismic source parameters.

Regarding the output categories of the classification model, existing models can be categorized into three groups: single classifiers, binary classifiers, and multiple classifiers. Initial research concentrated on single classifier models, aiming for accurate microseismic event detection without considering other non-microseismic signals. Due to blasting events being active sources and often mistaken for microseismic events, the number of binary classifiers dedicated to distinguishing between them increased [24]. As research advanced, noise events were gradually incorporated, leading to the emergence of multi-class classifier models targeting three or more classes. This encompasses not just microseismic and blasting events but also further divides noise events into categories such as drilling, ore drawing, electromagnetic interference, and human-made sound.

The development trajectory of microseismic signal identification methods highlights three significant trends: (1) incorporation of machine learning methods, (2) emergence of deep learning models, and (3) amalgamation of hybrid models and algorithm optimization. Each developmental stage is distinguished by a range of distinctive attributes. For instance, the introduction of machine learning methods alleviates the load of traditional manual identification and classification of microseismic signals, enhancing signal processing efficiency [25]. With the emergence of deep learning models, it becomes possible to cultivate more accurate classification models by leveraging extensive collected data, which substantially enhances accuracy and reliability [26]. For optimizing models and algorithms, attaining heightened computational efficiency while maintaining high accuracy is achievable. Alternatively, the focus shifts towards enhancing the model's generalization and robustness [27].

III. Classification of Machine Learning

Machine learning algorithms enable machines to extract patterns from extensive historical data and subsequently make predictions or distinctions about new samples. Remarkable advancements and implementations have been observed in specific domains including image recognition, signal processing, and computer vision [28]. In the context of microseismic signal recognition and classification, machine learning is categorized into two main branches: supervised learning [29] and unsupervised learning [30]. This classification is based on whether training samples are labeled or not. To elaborate, supervised learning pertains to input data with labels, while unsupervised learning pertains to data without labels.

A. *Supervised Learning*

In the realm of microseismic signal recognition and classification, several supervised learning algorithms are commonly employed, including logistic regression, plain Bayesian, SVM, decision trees, random forests, ANN, CNN, and others [31]. Upon analyzing and summarizing the predominant research endeavors in the existing literature, it becomes evident that a majority of these efforts focus on supervised learning, with CNN emerging as the most prevalent machine learning technique [32]. Notably, investigations extend to predicting time series evolutionary trends of microseismic parameters during rockburst development [33], depth detection of seismic sources [34], as well as studies in seismic event noise classification [35]. These efforts are closely trailed by advancements in CNN and the incorporation of hybrid methodologies [36].

Pu et al. [37] assessed the performance of ten widely used machine learning models for the recognition of microseismic and blast events. They employed five metrics to gauge these models' effectiveness. Their comprehensive evaluation indicated that the logistic regression model displayed the highest performance (97.5%). Kang et al. [38] introduced a deep belief network model for discerning microseismic events and blast events. By selecting nine typical source parameters as features, the model demonstrated superiority through a classification accuracy of 94.4%, outperforming SVM (86.15%) and Fisher (80.01%) classifiers. In a similar vein, Peng et al. [39] proposed an automated classification approach for finite sample microseismic records based on capsule networks (CapsNet). This model, when tested using the same dataset and compared to CNN and traditional machine learning methods, achieved an impressive accuracy of 99.2%, showcasing its proficiency, particularly in cases with limited training samples.

B. *Unsupervised Learning*

Unsupervised learning is a pivotal technique in data analysis, focusing on revealing underlying patterns and structures within unlabeled datasets [40]. This method forms the basis for various analytical tasks like clustering, dimensionality reduction, and visualization. Common algorithms include K-means, the Density-based clustering method, and PCA for dimensionality reduction. Additionally, deep learning techniques like deep belief networks (DBN) and self-coding algorithms (SCA) delve deeper into complex data representations. In contrast, unsupervised learning has been less well-studied, with K-means clustering being the dominant algorithm. Research topics range from the automatic classification of microseismic and explosive events [41], to studies of microseismic noise signals, and waveform-based studies.

Chen et al. [42] proposed an unsupervised machine learning algorithm for the automatic classification of microseismic data waveforms using classical K-means clustering. The feasibility of the algorithm is verified with synthetic and real microseismic data examples. The results show that the algorithm is effective in detecting the major waveforms in the data. Huang et al. [43] used a hierarchical clustering algorithm to achieve automatic identification of seismic signals. By examining four attributes, namely the short-term average and long-term average ratio, variance, and envelope, all seismic sampling points in the time domain were clustered into two categories. The feasibility of the method was demonstrated by applying it to an actual hydraulic fracturing microseismic dataset. Johnson et al. [44] used unsupervised machine learning to label five classes of non-smooth seismic noise commonly found in continuous waveforms. Chen et al. [45] used machine learning to help identify seismic waveforms in microseismic or seismic data. As supervised machine learning algorithms rely on a large amount of well-designed training data, this work uses unsupervised machine learning algorithms to cluster temporal samples into two groups, namely waveform points and non-waveform points. Experimental results show that the proposed method is more robust than STA/LTA method in extracting microseismic events even under moderate-intensity background noise. Saad et al. [46] propose an unsupervised method for automatically extracting waveform signals from continuous microseismic data. The algorithm was evaluated with several synthetic and field examples. The results show that the algorithm can successfully extract waveform signals in noisy environments with signal-to-noise ratios as low as 10 dB, and that the algorithm outperforms simple k-means and STA/LTA methods.

C. Machine Learning Development Stages

The development of machine learning in the field of microseismic signal recognition can be categorized into three stages: shallow learning, deep learning, and transfer learning. Fig.3 illustrates the distinctions among these three stages. Shallow learning, or traditional machine learning, employs simple algorithms to analyze and predict from data. Examples include linear regression, decision trees, SVM, and logistic regression. While effective for tasks with clear features, they may struggle with complex tasks requiring detection of intricate patterns. Deep learning, a subset of machine learning, utilizes neural networks with multiple layers to automatically learn complex patterns from raw data. Methods like CNN and RNNs have revolutionized fields like image recognition and natural language processing. Transfer learning leverages pre-trained models to improve performance on related tasks, making deep learning more accessible and reducing the need for large task-specific datasets.

Table 1 presents a comparison of machine learning techniques - Shallow Learning, Deep Learning, and Transfer Learning - in terms of accuracy, efficiency, and applicability. It also lists some common algorithms associated with each technique. In summary, shallow learning involves simple algorithms with limited computational layers, deep learning uses multi-layered neural networks to learn intricate patterns, and transfer learning enables models to leverage knowledge from one task to improve performance on another task.

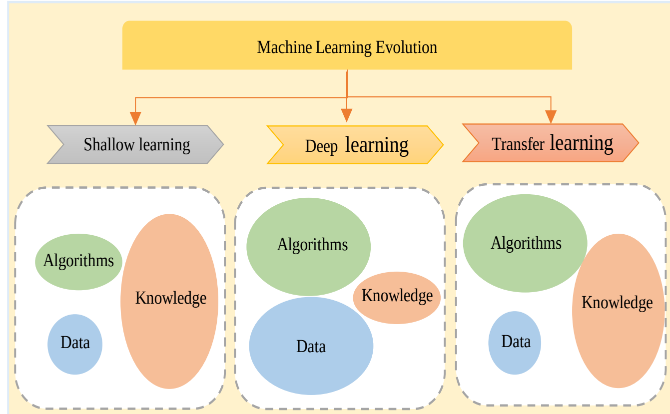

Fig. 3. Three stages of machine learning development

TABLE 1 COMPARATIVE ANALYSIS OF MACHINE LEARNING TECHNIQUES

Technique (Common algorithms)	**Accuracy**	**Efficiency**	**Applicability**
Shallow learning (LR, SVM, DT, RF, NV)	Lower accuracy [0.8, 0.9]	High efficiency with fast training and inference speed, low memory consumption	Widely applicable to tasks with clear features and relationships
Deep learning (CNN, RNN, DBN, LSTM, GAN)	Higher accuracy [0.9, 0.99]	Relatively lower efficiency with slower training and inference speed, higher memory consumption	Performs exceptionally well in complex tasks and those requiring the capture of intricate patterns or abstractions
Transfer learning (Pretrained models, e.g., AlexNet, GoogLeNet)	Variable accuracy [0.7, 0.99]	High efficiency by leveraging pre-trained models to reduce the need for task-specific data	Suitable for tasks with limited data availability, and can benefit from pre-trained models

IV. Discussion and Analysis

The fusion of advanced machine learning methods with the complexities of microseismic data has led to substantial progress, transforming how we approach microseismic event detection and comprehension.

A. Evolution of Machine Learning Paradigms

The realm of microseismic signal recognition has evolved through distinct phases of machine learning paradigms – shallow learning, deep learning, and transfer learning. Shallow learning, characterized by traditional algorithms, laid the initial foundation by extracting essential features from microseismic data. Deep learning, a transformative epoch, introduced neural networks capable of discerning intricate patterns, enabling improved accuracy and performance. Transfer learning, the latest frontier, leveraged pre-trained models to address data scarcity and domain adaptation challenges.

Deep learning models, particularly CNNs, have emerged as game-changers in microseismic signal classification. The ability of CNNs to automatically learn hierarchical features from raw data has proven vital. The study by Chen et al. [42] exemplifies how unsupervised learning can outperform traditional methods in extracting microseismic events, even under substantial noise. This highlights the significance of harnessing the latent potential within data.

The adoption of machine learning in microseismic signal recognition carries profound implications for both the industry and the research community. Efficient and accurate event detection, source localization, and event classification can lead to timely hazard alerts and informed decision-making in mining operations. The continuous evolution of algorithms and models empowers researchers to delve deeper into the intricacies of microseismic signals, unraveling invaluable insights into geological processes.

B. Challenges and Future

The identification and classification research of microseismic events currently faces the following challenges:

1) Data scarcity: The observation and recording of microseismic events require expensive equipment, resulting in a scarcity of labeled data available for research. This limitation hinders the training and validation of algorithm models, posing challenges to their accuracy and generalization capability.

2) Data imbalance: Positive instances (target events) in microseismic events are often much fewer in number than negative instances (non-target events or background noise). This data imbalance can lead to algorithm bias when handling imbalanced data, affecting its performance and robustness.

3) Noise interference: The accurate classification of microseismic signals is complicated by the presence of various sources of noise, including environmental and instrument noise.

4) Cross-domain adaptation: In practical applications, geographical and geological variations can introduce differences in the characteristics and background of microseismic events, posing challenges for transferring existing models to new regions or conditions.

To overcome these challenges, researchers are exploring and developing new methods and techniques. These include utilizing unsupervised learning for clustering, introducing deep learning models to extract intricate features, and leveraging transfer learning, among others. These efforts aim to enhance the accuracy of microseismic event identification and classification, thereby advancing research in related fields.

V. Conclusion

Incorporating machine learning into microseismic signal recognition and classification holds immense potential. The evolution from shallow to deep learning, along with the application of innovative techniques like unsupervised learning and transfer learning, has propelled development in this field. Machine learning plays a crucial role in microseismic signal analysis by providing mechanisms for accurate event identification and classification. Looking towards the future, advancements in data acquisition techniques offer opportunities for machine learning to address challenges such as data scarcity and domain adaptation, thus enhancing the accuracy and reliability of event recognition. The practical implications of applying machine learning in geological engineering and earth sciences are significant, as it can improve the precision and dependability of geological insights. The collaboration between machine learning and microseismic analysis promises a transformative impact on our understanding of subterranean events.

As we move forward, the convergence of machine learning and microseismic signal recognition presents fascinating possibilities. The amalgamation of diverse data sources, real-time processing capabilities, and advancements in transfer learning hold the potential to expand horizons. Advancing automation, refining accuracy, and bolstering resilience against noise are among the ambitions propelling ongoing research endeavors.

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