Discrimination Methods of Mine Inrush Water Source

Subjects: Engineering, Geological

Contributor: Donglin Dong , Jialun Zhang

Ensuring mining safety and efficiency relies heavily on identifying the source of mine water inrush. The standard methods used to pinpoint the origin of mine water inrush are systematically classified into various categories, encompassing hydrochemistry examination, water level and temperature analysis, geostatistical approaches, machine learning and deep learning methods, as well as the utilization of other analytical techniques.

mine inrush water source water source discrimination mining safety

1. Introduction

Water inrush incidents pose a formidable peril, imperiling both the safety of miners and the efficiency of coal production [1]. The specter of water inrush accidents looms large over the mining safety landscape worldwide, particularly in nations with robust coal industries, such as China, the United States, India, Iran and Australia [2][3][4]. Despite stringent regulatory measures, these catastrophes have tragically exacted a heavy toll in terms of lives lost and properties devastated over the years [5]. In light of their capricious nature, the ability to accurately and promptly distinguish water sources assumes paramount importance for mitigating water inrush incidents [6].

While the intellectual luminaries in this domain have undoubtedly made noteworthy strides, the rapid surge of information technology and the multidisciplinary paradigm necessitate a systematic audit and synthesis of the methodologies for discerning water origins within mine water inrush scenarios. The aim of this discourse is to address this exigency by comprehensively scrutinizing scholarly accomplishments related to water source discrimination in the context of mine water inrush. It orchestrates the systematic categorization of methods proffered by erudite minds in recent times, delineating the current status of research and the vistas for the evolution of water source discrimination in mine water inrush. The ultimate objective is to furnish a scientific scaffold for expeditious water source discrimination during water inrush events, thereby constituting a bedrock for judicious decision-making in the realm of preventing and managing water inrush accidents, safeguarding the security of coal mine operations.

The approach to water source discrimination within mine water inrush is underpinned by specific scientific doctrines, harnessed through diverse technical methodologies [1]. Through the collective endeavor of scholars spanning the globe, the pursuit of discriminating water sources in mine water inrush has witnessed substantive advancement. The dynamics of factors such as sedimentation, material interchanges, and geochemical terrains impact the behavior of water sources during their storage and transit across distinct strata.

The conventional hydrochemical method serves as the primary means of analyzing the primary ion content, which includes indicators such as Ca^{2+}, K, Na, $SO^{++}{}_4{}^{2-}$, HCO^{-}, Mg^{2+}, Cl^{-}, $CO_3{}^{2-}$, dissolved oxygen, alkalinity, acidity, pH value, and mineralization degree. This method plays a crucial role in determining the water quality classification of both the aquifer and the water influx [7][8][9][10][11][12][13][14][15][16][17][18][19][20][21][22][23].

However, it is important to recognize that the conventional chemical analysis method may not suffice in cases where water chemistry is complex. In such scenarios, alternative methods such as trace element analysis or environmental isotopes may be more appropriate [24][25][26][27][28]. The trace element method relies on measuring the content of specific trace elements in water samples and employing statistical analysis to discriminate the water source [24]. It offers high reliability and effectiveness even in cases of complex water chemistry.

Another approach to identifying water sources in water influx incidents is monitoring changes in water temperature or water level at the influx point. The water level and temperature method offer a direct and relatively straightforward approach, aiding in the analysis of water-bearing strata supply conditions and particularly effective for single-source groundwater surges [6]. However, its effectiveness may be limited when multiple aquifers or complex geological conditions are involved, and various factors can influence its accuracy.

The combination of the water level and temperature method with hydrochemical analysis has become prevalent in mining areas with high intensities. This integrated approach, along with the utilization of expandable recognition methods, GIS technology, and laser-induced fluorescence spectroscopy (LIF) technology, has led to significant progress in the identification of inrush water sources [29][30][31][32][33][34][35][36][37]. These advancements have enhanced efficiency, accuracy, and improved identification capabilities. LIF technology, known for its high sensitivity and rapid monitoring capabilities, significantly reduces the time re

In recent years, geostatistical methods have gained prominence as effective tools for water source discrimination in mine water inrush incidents. These methods involve the analysis of spatial relationships between water quality attributes, geological formations, and aquifer characteristics. Geostatistical simulation techniques, such as kriging, have been leveraged to generate potential spatial distribution maps of groundwater levels, electrical conductivity (EC), and permeability based on available data's spatial distribution characteristics [38][39][40][41][42][43]. This method allows for the prediction of the spatial dissemination of parameters, aiding in analyzing the interrelationships between parameters and their connections with geological structures.

As the depth of coal mining increases, it brings more serious risks to the safety of production from mixed groundwater from different aquifers on the coal mine gushing water, and also brings more data. Traditional analysis methods are not suitable for the huge amount of data [44]. The field of water source discrimination has experienced considerable development through advancements in computer technology and machine learning methods [44][45][46][47][48][49][50][51][52][53][54][55][56][57][58][59][60][61][62][63][64][65][66][67][68][69][70][71][72][73][74][75][76][77][78][79][80][81][82][83][84][85][86][87][88][89][90][91][92][93][94][95][96][97][98][99][100]. Artificial neural networks and deep learning algorithms, such as DNN and CNN, demonstrate remarkable abilities in determining the source of unknown water during inrush water inflow events. By establishing dynamic adaptive templates for automatic classification and discrimination of water sources, artificial intelligence enhances the efficiency and effectiveness of discrimination models.

To address the increasing risk of mixed groundwater from different aquifers in coal mines, it is crucial to utilize comprehensive discrimination methods and construct improved mixed discrimination models to promptly identify the source of mixed water during influx incidents [101]. The combination of multiple water source discrimination models can further optimize mine water influx source discrimination systems, allowing for accurate analysis and effective management of data samples. This comprehensive approach contributes to the prevention and control of water influx accidents in coal mines [92].

2. Traditional Techniques for Water Source Discrimination

Conventional chemical analysis of water is a widely utilized method for discriminating water sources in groundwater and inrush incidents [10]. This method involves analyzing major ions and comprehensive water quality indicators to determine the water quality types of the aquifer and the inrush water. Major ions such as Ca^{2+}, K, Na, $SO^{++}{}_4{}^{2-}$, HCO_3^-, Mg^{2+}, Cl^-, and CO_3^{2-} are examined, along with comprehensive indicators like dissolved oxygen, alkalinity, acidity, pH value, and mineralization.

In a specific study [10], hydrogeochemical analysis was conducted to identify non-conservative ions (K) and ion exchange (Ca^{+2+} and Mg^{2+}) in mine water. The PCA (Principal Component Analysis) method was employed to distinguish three components: seawater, freshwater, and brine. The proportions and distribution ranges of these components were summarized. A ternary mixing model was then used to quantify the proportion of each component, revealing that seawater accounted for 55% of the mine water, while freshwater constituted 15%. Based on these mixing proportions, along with the analysis of structural geology and engineering geological conditions, the potential flow pathways and primary storage of water were analyzed.

The trace element method is a reliable approach for discriminating water sources in inrush incidents, leveraging the characteristics and abundance of trace elements in water [24]. This method has been widely used in various studies. The findings of a specific research [24] indicate that seawater poses a significant threat to mining operations, particularly at deeper levels. The employed mixing model in the study exhibits high precision in reconstructing ion concentrations, demonstrates insensitivity to noisy data, and offers scalability for future data. This novel approach addresses the limitations of traditional methods, such as overlooking model scale, chemical reactions, circulation rates, as well as constraints in tracer element and end-member selection.

At the heart of this methodology lies a hydrochemical mixing model. This model is akin to blending various ingredients to create a unique concoction. In the context of hydrochemistry, it involves analyzing the chemical composition of groundwater samples collected from different depths. The composition reflects the “ingredients” or ions present in the water. By comparing these compositions and using mathematical techniques, the study sought to uncover the proportions of different water sources contributing to the overall groundwater composition. One novel aspect of the study was the incorporation of eigenvalue analysis. This technique, often used in fields like linear algebra and physics, was adapted to hydrochemical data. It acted as a guiding principle to determine the number of distinct end-members or sources contributing to the groundwater. Eigenvalue analysis essentially aids in identifying the fundamental components, allowing the researchers to decipher the specific sources of water in the system. Building upon these principles, the study developed a linear mixing algorithm using MATLAB. This algorithm played a pivotal role in calculating the ratios of each end-member within the groundwater composition.

The results of this investigation were revealing. The mixing model, coupled with eigenvalue analysis and PCA, unveiled five distinct end-members contributing to the groundwater composition. These sources included seawater, Quaternary water, freshwater, calcium-rich water, and magnesium-rich water. Each of these sources had varying levels of dominance at different depths within the mining region. Seawater emerged as a prominent water source, primarily influencing deeper levels. This finding underlines the criticality of addressing seawater incursion in mining operations.

One of the strengths of this methodology lies in its comprehensive nature. By integrating various analytical tools, the study was able to offer a nuanced understanding of the hydrochemical landscape. Additionally, the linear mixing algorithm's resilience against noisy data underscores its reliability.

In terms of applicability, this methodology finds its niche in scenarios where water inrush is a concern, such as mining operations. Its ability to provide quantitative insights into source contributions enhances decision-making processes. Furthermore, its adaptability to changing conditions and extendibility to future data collection makes it a valuable asset for continuous monitoring and analysis.

In conclusion, the study's approach to tracing water sources through hydrochemical mixing models presents a promising tool for understanding and managing water inrush in mining contexts. By blending mathematical techniques, statistical analysis, and hydrochemical data, the study illuminates the intricate hydrochemical landscape, offering crucial insights for ensuring safety and productivity in mining operations. While its strengths lie in its comprehensiveness and adaptability, careful consideration is required in complex geological scenarios. This methodology stands as a testament to the evolving synergy between science and real-world challenges.

Environmental isotopes, such as stable isotopes of oxygen and hydrogen, are also commonly used for discriminating inrush water sources in groundwater [25][26][27][28]. These isotopes, which do not typically react with other components, provide high reliability for tracing purposes. They offer advantages such as high accuracy and fast results. The isotopic composition of a water sample is compared with the isotopic composition of potential water sources to determine the water source. However, it is important to note that testing isotopes can be relatively costly.

In the initial phase, representative water samples were selected using stratified sampling and analyzed for water quality. Piper trilinear plots were utilized to analyze and extract typical water samples. PCA was then applied to analyze the hydrochemical ion concentrations of these typical water samples and extract critical principal component data. Subsequently, the Fisher classification model was trained using these principal component data to establish a water inrush source identification model for the mine area. The identification method of water inrush source can be used in coal mines and can be carried out according to **Figure 1**.

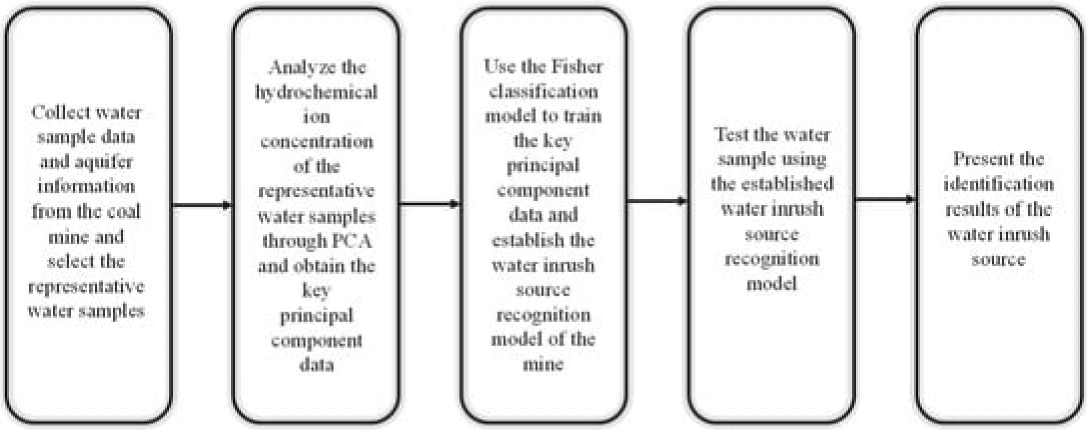

Figure 1. Application of water inrush source recognition model.

The research revealed significant differences in hydrochemical characteristics among different aquifers in the mining area, as well as variations in hydrochemical characteristics even among individual water samples within the same aquifer.

Conventional chemical analysis provides valuable hydrogeochemical information and is commonly employed to discriminate water sources in inrush incidents [7]. For instance, researchers have successfully used this method to discriminate the water sources of an inrush water influx in the Loess Plateau of China, identifying the upper aquifer as the origin due to coal seam exploitation in the area. However, it is important to note that the conventional chemical analysis method may not be sufficient to discriminate water sources in cases where water chemistry is complex.

The trace element method selects specific trace elements based on their unique characteristics and abundance in different water sources. The content of trace elements in the water sample is then measured, and statistical analysis is employed to discriminate the water source. This method demonstrates high reliability and can effectively discriminate inrush water sources even when the water chemistry is complex. However, it is important to note that interpreting the results of the trace element method may require a higher level of expertise.

Environmental isotopes provide reliable tracing capabilities and can yield accurate and prompt results. However, the testing cost of isotopes is relatively high, and the method may require specialized equipment and expertise. Additionally, its applicability may be limited in areas with restricted access to isotope testing facilities.

The environmental isotopes method adopted in this study [25] demonstrates strong applicability within the confines of the Fengfeng coalfield, offering a precise and relevant approach to address the intricate water contamination challenges unique to this region. By meticulously investigating interactions between abandoned mines, coal bedrock aquifers, and Ordovician Limestone aquifers, the methodology aligns perfectly with the region's hydrogeological intricacies. Its utilization of specialized techniques, such as stable isotope and sulfate isotope analysis, ensures a tailored understanding of the specific geochemical dynamics at play, resulting in solutions aligned with the immediate needs of the Fengfeng coalfield. This approach promises to deliver effective resolutions to the pressing environmental concerns specific to this locale.

While the environmental isotopes method's foundations stem from the Fengfeng coalfield, it holds the potential for broader relevance to regions grappling with similar water quality issues. Although certain adaptations may be requisite due to variations in geology, hydrogeology, and water chemistry, the core principles underpinning this methodology, such as examining water–rock interactions and utilizing isotope analysis, can be adopted. However, its broader success hinges on skillful customization, accounting for unique regional attributes. The methodology serves as a valuable template that can be reshaped and refined to effectively address comparable environmental challenges in diverse regions, fostering the preservation of water resources and ecosystems on a larger scale.

3. Advanced Techniques for Water Source Discrimination

3.1. Water Level and Water Temperature Method

The water level and water temperature method is commonly employed to identify the source of groundwater surges in mine water inrush incidents. This method consists of two main components: analyzing groundwater dynamics and studying groundwater temperature. Analyzing the response of the groundwater system to abrupt water level changes provides insights into the source of the surge, taking into account factors such as permeability of rock formations and aquifer geometry. The second component involves comparing groundwater temperature in the affected area with that in an unaffected area to identify the source of the surge. By combining the results of these analyses, a comprehensive understanding of the groundwater surge source can be obtained, especially in cases involving multiple aquifers or complex interactions between geological and anthropogenic factors.

The groundwater dynamics analysis revealed the evolution of the water outburst, including the stages of detection and drainage, water inflow, and groundwater level recovery. It identified a strong negative correlation between the variation in water inflow rate and karst water dynamics, while the relationship with pore water was minor. The study also found that karst water dynamics lagged behind water inflow dynamics. On the other hand, periodic fluctuations in pore water observation holes were related to rainfall and irrigation. It was noted that the registrability of karst aquifers varied based on factors such as permeability and the distance between the water inflow point and the observation borehole. While groundwater dynamics analysis can determine the water source, it cannot fully explain the deep mechanism of mine water surges.

Groundwater temperature analysis utilized steady-state ground temperature data to determine the depth and normothermic value of the normothermic layer. The ground temperature gradient was calculated for observation holes near the water outburst point using the linear relationship between ground temperature and burial depth. The authors applied a linear regression equation to estimate groundwater temperature in different types of groundwater. The study found that the water temperature measured at the outburst point closely matched that of the karst aquifer, suggesting that the main source of the outburst was karst water from the middle and lower parts of the Cambrian–Ordovician karst aquifer. The authors proposed grouting between the upper part of the karst aquifer and the water outburst point to block the source. However, they cautioned that the groundwater temperature discrimination method might not be applicable when the distance between two water-filled aquifers is short.

In conclusion, the Beiyangzhuang Mine case utilized three complementary methods to determine the source of the water outburst. Each method has its limitations, and a comprehensive analysis was conducted to arrive at a conclusion. When applying these methods in practical engineering scenarios, it is essential to consider the specific conditions and choose the appropriate method to determine the source of water surges, ensuring the safety and stability of the project.

3.2. Geostatistics Methods

The researchers employed diverse geostatistical techniques to discern the origins of mine water inrush. This segment aims to probe the utilization of various geostatistical methods for the identification of distinct sources of mine water inrush, augmenting the capacity to differentiate between different water origins. The section also furnishes an exhaustive delineation of each method's principles, applications, advantages, and constraints, presenting meticulous guidance for the establishment of a model to identify the sources of mine water inrush.

Cluster analysis amalgamates akin samples to unveil latent patterns. Q-type clustering categorizes initial data, while R-type clustering refines categorization for heightened precision. In this investigation, Q-type analysis is employed to classify raw water samples, succeeded by R-type analysis to refine identification precision. The initial phase of cluster analysis clusters akin samples based on proximity and subsequently clusters those with more pronounced distances [62].

PCA diminishes data dimensionality by metamorphosing original variables into uncorrelated principal components. It simplifies the model and amplifies computational efficiency. In this study, PCA is harnessed to engender independent indices that mirror hydrochemical insights. In this specific instance [71], PCA was employed to metamorphose the manifold original hydrochemical variables into a more compact set of principal components that collectively epitomize a substantial proportion of the variance inherent in the preliminary data. These ensuing principal components were subsequently deployed as independent variables in the formulation of a multifaceted logistic regression recognition model. The primary intent of this model was to prognosticate the probabilities of varied water inrush sources as dependent variables, contingent on the magnitudes of these principal components. Initially, hydrochemical data from water samples, encompassing concentrations of diverse ions, were amassed. Consecutively, the Principal Component Analysis (PCA) technique was administered to these data. PCA aims to truncate data dimensions by reshaping original variables into novel, uncorrelated principal components, thereby retaining maximal variance from the original data. The results showcased a noteworthy accomplishment. By assimilating PCA-derived principal components into the assembly of the multifaceted logistic regression model, the inquiry achieved a holistic recognition accuracy of 86.6%. This level of precision significantly outstripped that achieved by conventional methodologies. This outcome underscores PCA's adeptness in encapsulating the principal variability within the primal hydrochemical data by coalescing it into principal components.

Factor analysis delves into latent factors that underlie observed data and explicates the inter-variable covariance. Within this study [82], factor analysis is harnessed to preprocess training samples, accommodating the intrinsic associations among ions within coal mine waters.

Rough set theory categorizes and encapsulates data, ascertaining sample categories. It deals adeptly with uncertain and incomplete data, heightening the robustness of the model. The theory simplifies sample data, subsequently synergized with BP neural networks for water source identification. Rough set theory is a data analysis theory that is pertinent to the differentiation of water sources in mine breakouts by classifying and generalizing concepts and rules from a sample pool to roughly ascertain the category to which the sample belongs [96]. In this instance [96], rough set theory was initially employed to distill the sample data, followed by the application of the BP neural network for water source differentiation. A discriminative model for water sources was established based on the amalgamation of rough set theory and the BP neural network, and its performance was juxtaposed with the conventional BP neural network model. The results illustrated that the discriminating method based on rough set theory and BP neural network theory achieved a heightened discrimination accuracy of 92.5%, as opposed to the BP neural network method (82.5%).

The geostatistical simulation method leveraged random simulation techniques to engender potential spatial distribution maps of groundwater levels, EC, and permeability grounded in the spatial distribution characteristics of the available data [39]. The essence of this method lies in employing simulation to unveil the spatial fluctuations of parameters in the mining milieu. The application scope of the geostatistical simulation method encompasses predicting the spatial dissemination of parameters, aiding in analyzing the interrelations between parameters and their connections with geological structures.

The Multi-Criteria Decision Analysis (MCDA) method was engaged to holistically contemplate the influences of varied parameters on the selection of new groundwater well locations. This method, predicated on attributing weights to multiple criteria, facilitates the comparison and quantitative assessment of diverse decision alternatives, culminating in the determination of the optimal solution [39]. The fundamental principle underpinning MCDA lies in striking an equilibrium between different criteria and thoroughly accounting for their relative significance to arrive at a comprehensive decision. This methodology finds pertinence in scenarios where the objective entails choosing the most suitable course of action among multifarious alternatives, thereby maximizing contentment across a plethora of criteria. While this approach is brought to bear on the challenge of selecting new groundwater well locations, its foundational principles bear semblance to those employed in identifying sources of inrush water. Consequently, it can serve as a methodological point of reference for such pursuits.

The issue of water inrush in mining operations presents a formidable challenge, necessitating innovative solutions. A recent inquiry ventured into this quandary through a combination of hydrogeological analysis and a multi-criteria decision analysis (MCDA) framework. This concerted effort aimed to pinpoint optimal well positions for the effective management of groundwater influx.

The methodology of the study adopted a multifaceted stance. The investigative journey commenced with an examination of the histogram and variogram of groundwater levels. The histogram unveiled a bimodal distribution, attributed to the strategic discharge from pumping wells strategically placed in the central and eastern sectors of the excavation site. The resultant cone of depression engendered by these wells yielded disparate groundwater levels across the site, with an average groundwater level of 1654.1 m above sea level (asl).

Subsequently, the geostatistical stochastic simulations delved into the spatial distribution of groundwater levels, electrical conductivity (EC), and transmissivity. These simulations provided a comprehensive panorama of the variability of these parameters across the mining expanse. A conspicuous correlation materialized among these variables, unveiling the intricate interplay between hydrogeological attributes and water quality.

3.3. Machine Learning Methods

The researchers employed diverse machine learning techniques to discern the origins of mine water inrush. Initially, they scrutinized the chemical composition of standard components and inrush water samples from aquifers. Subsequently, they selected appropriate discriminant functions rooted in statistical theory and constructed a discriminant model.

Three widely recognized models, namely the Fisher discriminant model, distance discriminant model, and Bayesian discriminant model, were employed to differentiate various water sample types by identifying optimal discriminant functions through measured water sample data [52][57][72]. The Fisher discriminant model classifies samples by identifying a linear discriminant function that best segregates two sample groups.

The distance discriminant model categorizes samples based on calculated distances, grouping closer samples into the same category. Jiang [57] proposed an extensive stepwise discriminant approach to identify water sources in a multifaceted multiaquifer mine. The method employed characteristic ion contrasts, ion proportional coefficients, and the Fisher discriminant method to distinguish between aquifers with varying water chemistry attributes. The method's effectiveness was attested by its successful application to the Xinji No. 2 mine, implying its potential suitability for akin hydrogeological contexts.

Support vector machine (SVM), a statistical learning model, erects an optimal hyperplane in the sample space to achieve superior generalization ability and prediction accuracy, well-suited for small sample data [65]. Wei [65] amalgamated several algorithms including the Fisher identification method, self-organizing correlation method (SOM), improved principal component analysis method (PCSOM), and the grey wolf algorithm (GWO)-optimized support vector machine (GWOSVM). The results demonstrated the efficacy of the PCSOM algorithm in diminishing information overlap between discriminant indices, streamlining model structure, and refining algorithm efficiency. Moreover, the grey wolf algorithm optimized the penalty factor 'c' and kernel parameter 'g' of the support vector machine, yielding faster and more stable parameter optimization, thus leading to enhanced discrimination outcomes.

Logistic regression analysis, a statistical machine learning method, fabricates classification models for water source discrimination issues [71]. This method can distill primary influencing factors from diverse water chemistry indicators and is pertinent for probing probability concerns pertaining to the occurrence of the dependent variable.

Evidence theory, adept at handling uncertain information, finds application in multi-sensor information fusion problems [82]. By establishing a recognition framework based on the D-S evidence theory, the researchers formulated a fusion decision model for water inrush. This model integrated indices like aquifer permeability, geological structure, aquitard properties, hydraulic pressure, and mining pressure as pieces of evidence, achieving effective and feasible results for predicting water inrush.

3.4. Deep Learning Methods

The combination of neural networks and computer algorithms is a hot topic of current research, in which neural networks are widely used to discriminate water sources for mine water bursts. Standard artificial neural network models include BP, RBF, ELM, and Elman neural networks [94]. These models learn the features of sample data and build mathematical models to achieve the classification and discrimination of water sources [82]. Deep learning algorithms are the development of artificial neural networks and play an essential role in classifying and discriminating mixed water samples from multiple sources. Standard deep learning algorithms include the deep neural network DNN and convolutional neural network CNN network analysis methods [97]. Ant colony and genetic algorithms are mainly used for function and combinatorial optimization of discriminative models [91]. The ant colony algorithm imitates the behavior of ants in searching for food and optimizes the answer to the problem by simulating the information exchange and cooperation of ants in searching for food. Genetic algorithms are computational methods that simulate natural selection and genetic mechanisms and continuously optimize the answers to solving problems by selecting, crossing, and mutating the best individuals in the colony [85][91]. In the context of identifying water sources in mines, particle swarm optimization is another algorithm that has gained attention due to its ability to solve complex optimization problems [69]. In particle swarm optimization, a group of particles (potential solutions) move through the search space and update their positions based on their own previous best solution and the best solution of their neighbors. The Sparrow Search Algorithm (SSA) is a novel swarm intelligence algorithm that can be used to solve optimization problems [69]. The algorithm is inspired by the swarm behavior of finches, in which each sparrow cooperates to find food through simple communication and adaptation. SSA analyzes the behavior of finches, represents the problem as a fitness function, and then applies multiple sparrows to represent different solutions to the problem to find a better solution continuously.

4. Conclusions

In conclusion, the identification of water sources in mine water inrushes requires the use of various methods, including water level and temperature analysis, hydrochemistry, geostatistical methods discrimination, machine learning and deep learning discrimination, and other analytical methods. Selecting the appropriate method depends on the specific hydrogeological conditions at the water inrush point and requires the establishment of a comprehensive water sample database to ensure accurate identification.

With the shift towards deep mining in many mines, the hydrogeological conditions become more complex, and groundwater mixing becomes more prevalent. The advancement of computer science and mathematical algorithms has enabled the development of interdisciplinary discrimination analysis methods for rapid identification of multiple water sources at water inrush points. Artificial neural networks and deep learning algorithms, which are part of the field of artificial intelligence and machine learning, have emerged as hotspots and offer new approaches for multi-source water inrush discrimination.

Furthermore, the combination of microbiological technology or fiber optic technology with water inrush source identification methods, as well as full-spectrum ion identification technology and fluorescence spectroscopy identification technology for dissolved organic matter, are trends that researchers will likely explore in future studies. These advancements will contribute to improving the accuracy and efficiency of water source identification in mine water inrushes.

Undoubtedly, the fusion of artificial intelligence (AI), heightened computational prowess, internet-based programming, and intelligent data acquisition mechanisms presents a profound opportunity to reconfigure the landscape of inrush water identification and preemptive measures. This confluence of technological marvels possesses the potential to substantially elevate the precision, velocity, and efficacy in addressing potential inrush water occurrences across diverse sectors including mining, construction, and infrastructure oversight. The amalgamation of AI, amplified computational prowess, online programming, and astute data acquisition mechanisms bears the capacity to metamorphose the approach taken by industries toward inrush water events. Through the adept utilization of these technological enablers, industries can ascend to a heightened state of preparedness, curtail the reverberations of such incidents, and thereby amplify overall safety and operational dexterity.

References

1. Wu, M.; Ye, Y.; Hu, N.; Wang, Q.; Tan, W. Visualization Analysis and Progress of Mine Water Inrush Disaster-Related Research. Mine Water Environ. 2022, 41, 599–613.
2. Chen, Y.; Liu, R.; Barrett, D.; Gao, L.; Zhou, M.; Renzullo, L.; Emelyanova, I. A Spatial Assessment Framework for Evaluating Flood Risk under Extreme Climates. Sci. Total. Environ. 2015, 538, 512–523.
3. Dash, A.K.; Bhattacharjee, R.M.; Paul, P.S. Lessons Learnt from Indian Inundation Disasters: An Analysis of Case Studies. Int. J. Disaster Risk Reduct. 2016, 20, 93–102.
4. Gharaat, M.J.; Mohammadi, Z.; Assari, A.; Rezanezhad, F. Groundwater Circulation and Origin of Salinity in a Multi-Aquifer System: The Gohar-Zamin Mining Area, Iran. Mine Water Environ. 2022, 41, 996–1014.

5. Bringemeier, D. Inrush and Mine Inundation—A Real Threat to Australian Coal Mines. In Proceedings of the International Mine Water Association Annual Conference, Bunbury, Australia, 29 September–4 October 2012; Volume 30.
6. Wu, Q.; Mu, W.; Xing, Y.; Qian, C.; Shen, J.; Wang, Y.; Zhao, D. Source discrimination of mine water inrush using multiple methods: A case study from the Beiyangzhuang Mine, Northern China. Bull. Eng. Geol. Environ. 2019, 78, 469–482.
7. Sui, W.; Liu, J.; Yang, S.; Chen, Z.; Hu, Y. Hydrogeological analysis and salvage of a deep coalmine after a groundwater inrush. Environ. Earth Sci. 2011, 62, 735–749.
8. Bi, Y.; Wu, J.; Zhai, X.; Shen, S.; Tang, L.; Huang, K.; Zhang, D. Application of Partial Least Squares-Discriminate Analysis Model Based on Water Chemical Compositions in Identifying Water Inrush Sources from Multiple Aquifers in Mines. Geofluids 2021, 2021, 1–17.
9. Duan, X.; Ma, F.; Gu, H.; Guo, J.; Zhao, H.; Liu, G.; Liu, S. Identification of Mine Water Sources Based on the Spatial and Chemical Characteristics of Bedrock Brines: A Case Study of the Xinli Gold Mine. Mine Water Environ. 2022, 41, 126–142.
10. Duan, X.; Ma, F.; Guo, J.; Zhao, H.; Gu, H.; Liu, S.; Sun, Q. Source Identification and Quantification of Seepage Water in a Coastal Mine, in China. Water 2019, 11, 1862.
11. Huang, P.; Gao, H.; Su, Q.; Zhang, Y.; Cui, M.; Chai, S.; Li, Y.; Jin, Y. Identification of mixing water source and response mechanism of radium and radon under mining in limestone of coal seam floor. Sci. Total Environ. 2023, 857, 159666.
12. Huang, P.; Wang, X. Piper-PCA-Fisher Recognition Model of Water Inrush Source: A Case Study of the Jiaozuo Mining Area. Geofluids 2018, 2018, 9205025.
13. Huang, P.-h.; Wang, X.-y.; Han, S.-m. Recognition model of groundwater inrush source of coal mine: A case study on Jiaozuo coal mine in China. Arab. J. Geosci. 2017, 10, 1–8.
14. Mali, S.; Jafari, H.; Jahanshahi, R.; Bagheri, R. Groundwater Source Identification and Flow Model of the Dareh-Zar Copper Mine in Central Iran by Chemo-isotopic Techniques. Mine Water Environ. 2022, 41, 921–937.
15. Wang, D.; Shi, L. Source identification of mine water inrush: A discussion on the application of hydrochemical method. Arab. J. Geosci. 2019, 12, 58.
16. Wang, X.; Ji, H.; Wang, Q.; Liu, X.; Huang, D.; Yao, X.; Chen, G. Divisions based on groundwater chemical characteristics and discrimination of water inrush sources in the Pingdingshan coalfield. Environ. Earth Sci. 2016, 75, 872.
17. Wang, Y.; Shi, L.; Wang, M.; Liu, T. Hydrochemical analysis and discrimination of mine water source of the Jiaojia gold mine area, China. Environ. Earth Sci. 2020, 79, 123.

18. Wu, Y.; Lin, Y.; Pan, G. Discrimination of bursting water source by hydrochemical and stable isotope method. In Proceedings of the International Mine Water Association Annual Conference on Reliable Mine Water Technology, Golden, CO, USA, 6–9 August 2013; pp. 911–916.
19. Yang, J.; Dong, S.; Wang, H.; Li, G.; Wang, T.; Wang, Q. Mine Water Source Discrimination Based on Hydrogeochemical Characteristics in the Northern Ordos Basin, China. Mine Water Environ. 2021, 40, 433–441.
20. Zhang, H.; Xu, G.; Chen, X.; Wei, J.; Yu, S.; Yang, T. Hydrogeochemical Characteristics and Groundwater Inrush Source Identification for a Multi-aquifer System in a Coal Mine. Acta Geol. Sin. Engl. Ed. 2019, 93, 1922–1932.
21. Zhang, J.; Chen, L.; Chen, Y.; Ge, R.; Ma, L.; Zhou, K.; Shi, X. Discrimination of water-inrush source and evolution analysis of hydrochemical environment under mining in Renlou coal mine, Anhui Province, China. Environ. Earth Sci. 2020, 79, 61.
22. Zhang, J.; Yao, D. Hydrogeochemical characteristics of coal mine based on box-plot and its application in water inrush source identification. Energy Sources Part Recovery Util. Environ. Eff. 2020, 35, 4.
23. Zuo, W.; Wang, G.; Li, J.; Gao, L. Water Source Determination of Mine Inflow Based on Non-Linear Method and Hydrochemical Characteristics. In Proceedings of the International Conference on Energy, Environment and Sustainable Development (ICEESD 2011), 21–23 October 2011; Shanghai University of Electric Power: Shanghai, China, 2012; p. 92.
24. Gu, H.; Ni, H.; Ma, F.; Liu, G.; Hui, X.; Cao, J. Using mixing model to interpret the water sources and ratios in an under-sea mine. Nat. Hazards 2020, 104, 1705–1722.
25. Hao, C.; Zhang, W.; Tang, J.; Gui, H. Water-Rock Interaction And Stable Isotopes (S-34, O-18) As Geochemical Tracing Source Of Sulfate In Abandoned Mine Water: A Case Study Of The Fengfeng Coalfield In North China. Fresenius Environ. Bull. 2021, 30, 1527–1537.
26. Guan, Z.; Jia, Z.; Zhao, Z.; You, Q. Identification of inrush water recharge sources using hydrochemistry and stable isotopes: A case study of Mindong No. 1 coal mine in north-east Inner Mongolia, China. J. Earth Syst. Sci. 2019, 128, 1–12.
27. Gu, H.; Ma, F.; Guo, J.; Li, K.; Lu, R. Assessment of Water Sources and Mixing of Groundwater in a Coastal Mine: The Sanshandao Gold Mine, China. Mine Water Environ. 2018, 37, 351–365.
28. Duan, X.; Ma, F.; Zhao, H.; Guo, J.; Gu, H.; Lu, R.; Liu, G. Determining mine water sources and mixing ratios affected by mining in a coastal gold mine, in China. Environ. Earth Sci. 2019, 78, 299.
29. Dai, G.; Xue, X.; Xu, K.; Dong, L.; Niu, C. A GIS-based method of risk assessment on no. 11 coal-floor water inrush from Ordovician limestone in Hancheng mining area, China. Arab. J. Geosci. 2018, 11, 714.

30. Jiang, Q.; Zhao, W.; Zheng, Y.; Wei, J.; Wei, C. A source discrimination method of mine water-inrush based on 3d spatial interpolation of rare classes. Arch. Min. Sci. 2019, 64, 321–333.
31. Zeng, Y.; Wu, Q.; Liu, S.; Zhai, Y.; Lian, H.; Zhang, W. Evaluation of a coal seam roof water inrush: Case study in the Wangjialing coal mine, China. Mine Water Environ. 2018, 37, 174–184.
32. He, C.-y.; Zhou, M.-r.; Yan, P.-c. Application of the Identification of Mine Water Inrush with LIF Spectrometry and KNN Algorithm Combined with PCA. Spectrosc. Spectr. Anal. 2016, 36, 2234–2237.
33. Hu, F.; Zhou, M.; Yan, P.; Li, D.; Lai, W.; Zhu, S.; Wang, Y. Selection of characteristic wavelengths using SPA for laser induced fluorescence spectroscopy of mine water inrush. Spectrochim. Acta Part A-Mol. Biomol. Spectrosc. 2019, 219, 367–374.
34. Yan, P.-c.; Zhou, M.-r.; Liu, Q.-m.; Zhang, K.-y.; He, C.-y. Research on the Source Identification of Mine Water Inrush Based on LIF Technology and SIMCA Algorithm. Spectrosc. Spectr. Anal. 2016, 36, 243–247.
35. Zhou, M.; Yan, P. Research of mine water source identification based on LIF technology. In Proceedings of the 8th International Symposium on Advanced Optical Manufacturing and Testing Technology (AOMATT)—Optical Test, Measurement Technology, and Equipment, Suzhou, China, 26–29 April 2016.
36. Zhou, M.-r.; Hu, F.; Yan, P.-c.; Liu, D. Laser Induced Fluorescence Spectrum Analysis of Water Inrush in Coal Mine Based on FCM. Spectrosc. Spectr. Anal. 2018, 38, 1572–1576.
37. Zhou, M.-r.; Song, H.-p.; Hu, F.; Lai, W.-h.; Wang, J.-g. Application of Spectral Clustering and LIF in Recognition of Mine Water Inrush Source Types. Spectrosc. Spectr. Anal. 2021, 41, 435–440.
38. Assari, A.; Mohammadi, Z. Assessing Flow Paths in a Karst Aquifer Based on Multiple Dye Tracing Tests Using Stochastic Simulation and the MODFLOW-CFP Code. Hydrogeol. J. 2017, 25, 1679–1702.
39. Assari, A.; Mohammadi, Z. Combined Use of Geostatistics and Multi-Criteria Decision Analysis to Determine New Pumping Well Locations in the Gol-Gohar Open Pit Mine, Iran. Mine Water Environ. 2017, 36, 283–298.
40. Gharaat, M.J.; Mohammadi, Z.; Rezanezhad, F. Distribution and Origin of Potentially Toxic Elements in a Multi-Aquifer System. Environ. Sci. Pollut. Res. 2020, 27, 43724–43742.
41. Adeli, M.; Mohammadi, Z.; Keshavarzi, B.; Amjadian, K.; Kafi, M. Heavy Metal(Loid) Pollution of a Hard-Rock Aquifer: Evidence, Distribution, and Source. Environ. Sci. Pollut. Res. 2021, 28, 34742–34761.
42. Malczewski, J. Local Weighted Linear Combination: Local Weighted Linear Combination. Trans. GIS 2011, 15, 439–455.

43. De Avila, H.M.; Júnez-Ferreira, H.E.; Gonzalez-Trinidad, J.; Esteller-Alberich, M.V.; Silva-Ávalos, R.U.; Davila-Hernandez, S.; Cazares-Escareño, J.; Bautista-Capetillo, C.F. Schematization of Converging Groundwater Flow Systems Based on 3D Geostatistics. Water 2022, 14, 3169.
44. Sun, L.H. Statistical analysis of hydrochemistry of groundwater and its implications for water source identification: A case study. Arab. J. Geosci. 2014, 7, 3417–3425.
45. Wang, X.; Zhao, W.; Liu, X.; Wang, T.; Zhang, J.; Guo, J.; Cheng, G.; Zhang, B. Identification of water inrush source from coalfield based on entropy weight-fuzzy variable set theory. J. China Coal Soc. 2017, 42, 2433–2439.
46. Wen, T.; Zhang, B.; Shao, L. Research on prediction of mine water inrush source identification-Xinzhuangzi coalfield as an example. China Saf. Sci. J. 2014, 24, 100–106. (In Chinese)
47. Ma, D.; Duan, H.; Cai, X.; Li, Z.; Li, Q.; Zhang, Q. A global optimization-based method for the prediction of water inrush hazard from mining floor. Water 2018, 10, 1618.
48. Zhang, R.; Qian, J.; Ma, L.; Qin, H. Application of extension identification method in mine water-bursting source discrimination. J. China Coal Soc. 2009, 34, 33–38. (In Chinese)
49. Zhou, J.; Shi, X.; Wang, H. Water-bursting source determination of mine based on distance discriminant analysis model. J. China Coal Soc. 2010, 35, 278–282. (In Chinese)
50. Bi, Y.; Wu, J.; Zhai, X.; Wang, G.; Shen, S.; Qing, X. Discriminant analysis of mine water inrush sources with multi-aquifer based on multivariate statistical analysis. Environ. Earth Sci. 2021, 80, 144.
51. Chen, J.; Yang, R. Analysis of mine water inrush accident based on FTA. In Proceedings of the 2nd International Conference on Challenges in Environmental Science and Computer Engineering (CESCE), Haikou, China, 14–15 December 2011; pp. 1550–1554.
52. Dong, D.; Chen, Z.; Lin, G.; Li, X.; Zhang, R.; Ji, Y. Combining the Fisher Feature Extraction and Support Vector Machine Methods to Identify the Water Inrush Source: A Case Study of the Wuhai Mining Area. Mine Water Environ. 2019, 38, 855–862.
53. Gong, F.; Fu, Z.; Lu, J. Headstream identification of mine water-inrush source based on multivariate discriminant analysis method. Disaster Adv. 2013, 6, 444–450.
54. Güler, C.; Thyne, G.; McCray, J.; Turner, K. Evaluation of graphical and multivariate statistical methods for class ification of water chemistry data. Hydrogeol. J. 2002, 10, 455–474.
55. Hu, Y.; Huang, P.; Gao, H.; Su, Q. State of the Practice Worldwide: HCA-PCA-EWM Discrimination Model of Water Inrush Source in Mines. Ground Water Monit. Remediat. 2022, 42, 67–76.
56. Huang, P.; Yang, Z.; Wang, X.; Ding, F. Research on Piper-PCA-Bayes-LOOCV discrimination model of water inrush source in mines. Arab. J. Geosci. 2019, 12, 334.

57. Jiang, C.; An, Y.; Zheng, L.; Huang, W. Water Source Discrimination in a Multiaquifer Mine Using a Comprehensive Stepwise Discriminant Method. Mine Water Environ. 2021, 40, 442–455.
58. Ju, Q.; Hu, Y. Source identification of mine water inrush based on principal component analysis and grey situation decision. Environ. Earth Sci. 2021, 80, 157.
59. Li, B.; Wu, Q.; Liu, Z. Identification of Mine Water Inrush Source Based on PCA-FDA: Xiandewang Coal Mine Case. Geofluids 2020, 2020, 8.
60. Liu, G.; Ma, F.; Liu, G.; Zhao, H.; Guo, J.; Cao, J. Application of Multivariate Statistical Analysis to Identify Water Sources in A Coastal Gold Mine, Shandong, China. Sustainability 2019, 11, 3345.
61. Liu, Q.; Sun, Y.; Xu, Z.; Xu, G. Application of the comprehensive identification model in analyzing the source of water inrush. Arab. J. Geosci. 2018, 11, 189.
62. Liu, W.; Yu, J.; Shen, J.; Zheng, Q.; Han, M.; Hu, Y.; Meng, X. Application of Clustering and Stepwise Discriminant Analysis Based on Hydrochemical Characteristics in Determining the Source of Mine Water Inrush. Geofluids 2021, 2021, 6670645.
63. Qian, J.; Wang, L.; Ma, L.; Lu, Y.; Zhao, W.; Zhang, Y. Multivariate statistical analysis of water chemistry in evaluating groundwater geochemical evolution and aquifer connectivity near a large coal mine, Anhui, China. Environ. Earth Sci. 2016, 75, 747.
64. Wang, D.; Ju, Q.; Wang, Y.; Hu, Y.; Liu, Q.; Chai, H.; Liu, Y. Source identification of mine water inrush based on the exponential whitenization function and the grey situation decision model. Energy Explor. Exploit. 2022, 40, 1217–1235.
65. Wei, Z.; Dong, D.; Ji, Y.; Ding, J.; Yu, L. Source Discrimination of Mine Water Inrush Using Multiple Combinations of an Improved Support Vector Machine Model. Mine Water Environ. 2022, 41, 1106–1117.
66. Wu, Q.; Zhou, W. Prediction of groundwater inrush into coal mines from aquifers underlying the coal seams in China: Vulnerability index method and its construction. Environ. Geol. 2008, 56, 245–254.
67. Xue, W.; Hou, E.; Zhao, X.; Ye, Y.; Tsangaratos, P.; Ilia, I.; Chen, W. Discriminant Analysis of Water Inrush Sources in the Weibei Coalfield, Shaanxi Province, China. Water 2023, 15, 453.
68. Yan, B.; Ren, F.; Cai, M.; Qiao, C. Bayesian model based on Markov chain Monte Carlo for identifying mine water sources in Submarine Gold Mining. J. Clean. Prod. 2020, 253, 120008.
69. Yan, P.; Shang, S.; Zhang, C.; Yin, N.; Zhang, X.; Yang, G.; Zhang, Z.; Sun, Q. Research on the Processing of Coal Mine Water Source Data by Optimizing BP Neural Network Algorithm with Sparrow Search Algorithm. IEEE Access 2021, 9, 108718–108730.
70. Yan, Z.; Han, J.; Yu, J.; Yang, Y. Water inrush sources monitoring and identification based on mine IoT. Concurr. Comput. Pract. Exp. 2019, 31, e4843.

71. Zhang, H.; Xing, H.; Yao, D.; Liu, L.; Xue, D.; Guo, F. The multiple logistic regression recognition model for mine water inrush source based on cluster analysis. Environ. Earth Sci. 2019, 78, 612.
72. Zhang, H.; Yao, D. The Bayes Recognition Model for Mine Water Inrush Source Based on Multiple Logistic Regression Analysis. Mine Water Environ. 2020, 39, 888–901.
73. Zhang, J.; Yao, D.; Su, Y. Multivariate matrix model for source identification of inrush water: A case study from Renlou and Tongting coal mine in northern Anhui province, China. In Proceedings of the 3rd International Conference on Advances in Energy Resources and Environment Engineering (ICAESEE), Harbin, China, 8–10 December 2017.
74. Zhao, X.; Xu, Z.; Sun, Y. Identification of Mine Water Source Based on AHP-Entropy and Set Pair Analysis. Geofluids 2022, 2022, 3862746.
75. Zhou, M.-r.; Li, D.-t.; Hu, F.; Lai, W.-h.; Wang, Y.; Zhu, S. Research of the AdaBoost Arithmetic in Recognition and Classifying of Mine Water Inrush Sources Fluorescence Spectrum. Spectrosc. Spectr. Anal. 2019, 39, 485–490.
76. CAO, Q.-K. Risk evaluation of water inrush from coal floor based on fuzzy support vector machine. J. China Coal Soc. 2011, 36, 633–637. (In Chinese)
77. Chen, H.; Li, X.; Liu, A.; Peng, S. Identifying of mine water inrush sources by Fisher discriminant analysis method. J. Cent. South Univ. (Sci. Technol.) 2009, 40, 1114–1120. (In Chinese)
78. Gong, F.; Lu, J. Recognition method of mine water inrush sources based on the principal element analysis and distance discrimination analysis. J. Min. Saf. Eng. 2014, 31, 236–242. (In Chinese)
79. Huang, P.; Chen, J. Fisher indentify and mixing model based on multivariate statistical analysis of mine water inrush sources. J. China Coal Soc. 2011, 36, 131–136. (In Chinese)
80. Lu, J.-T.; Li, X.-B.; Gong, F.-Q.; Wang, X.-R.; Liu, J. Recognizing of mine water inrush sources based on principal components analysis and fisher discrimination analysis method. Zhongguo Anquan Kexue Xuebao 2012, 22, 109–115. (In Chinese)
81. Qin, C.; Liang, Q.; Pan, L.; Zhang, L.; Ma, Y. Rapid discrimination of mine water inrush source based on rough set theory. Min. Saf. Environ. Prot. 2014, 41, 81–84. (In Chinese)
82. Han, J.; Shi, L.; Zhai, P.; Li, S.; Yu, X. Application of multi-attribute decision and DS evidence theory to water-inrush decision of floor in mining. Chin. J. Rock Mech. Eng. 2009, 28, 3727–3732. (In Chinese)
83. Chen, Y.; Tang, L.; Zhu, S. Comprehensive study on identification of water inrush sources from deep mining roadway. Environ. Sci. Pollut. Res. 2022, 29, 19608–19623.
84. Wang, Y.; Zhou, M.; Yan, P.; Hu, F.; Lai, W.; Yang, Y.; Zhang, Y. A rapid identification model of mine water inrush based on extreme learning machine. J. China Coal Soc. 2017, 42, 2427–2432. (In Chinese)

85. Zhang, D.; Meng, L.; Dong, F.; Liu, X.; Shao, Q. Study on GA-SVM for mine water inrush source identification. Coal Technol. 2018, 37, 144–147. (In Chinese)

86. Zhu, C.; Qian, J.; Zhou, X.; Ma, L. Water-inrush source discrimination with BP neural network in Pansan Mine. J. Anhui Inst. Arch. Ind (Nat. Sci. Ed.) 2010, 18, 35–38. (In Chinese)

87. Fang, B. Method for Quickly Identifying Mine Water Inrush Using Convolutional Neural Network in Coal Mine Safety Mining. Wirel. Pers. Commun. 2022, 127, 945–962.

88. Ji, Y.; Dong, D.; Gao, J.; Wei, Z.; Ding, J.; Hu, Z. Source Discrimination of Mine Water Inrush Based on Spectral Data and EGA-PNN Model: A Case Study of Huangyuchuan mine. Mine Water Environ. 2022, 41, 583–593.

89. Ji, Y.; Dong, D.; Mei, A.; Wei, Z. Study on key technology of identification of mine water inrush source by PSO-LightGBM. Water Supply 2022, 22, 7416–7429.

90. Jiang, C.; Zhu, S.; Hu, H.; An, S.; Su, W.; Chen, X.; Li, C.; Zheng, L. Deep learning model based on big data for water source discrimination in an underground multiaquifer coal mine. Bull. Eng. Geol. Environ. 2022, 81, 26.

91. Li, X.; Dong, D.; Liu, K.; Zhao, Y.; Li, M. Identification of Mine Mixed Water Inrush Source Based on Genetic Algorithm and XGBoost Algorithm: A Case Study of Huangyuchuan Mine. Water 2022, 14, 2150.

92. Lin, G.; Jiang, D.; Dong, D.; Fu, J.; Li, X. A Multilevel Recognition Model of Water Inrush Sources: A Case Study of the Zhaogezhuang Mining Area. Mine Water Environ. 2021, 40, 773–782.

93. Montes-Atenas, G.; Seguel, F.; Valencia, A.; Bhatti, S.M.; Khan, M.S.; Soto, I.; Yoma, N.B. Predicting bubble size and bubble rate data in water and in froth flotation-like slurry from computational fluid dynamics (CFD) by applying deep neural networks (DNN). Int. Commun. Heat Mass Transf. 2016, 76, 197–201.

94. Yan, P.-c.; Shang, S.-h.; Zhang, C.-y.; Zhang, X.-f. Classification of Coal Mine Water Sources by Improved BP Neural Network Algorithm. Spectrosc. Spectr. Anal. 2021, 41, 2288–2293.

95. Yan, P.-c.; Zhang, X.-f.; Shang, S.-h.; Zhang, C.-y. Research on Mine Water Inrush Identification Based on LIF and LSTM Neural Network. Spectrosc. Spectr. Anal. 2022, 42, 3091–3096.

96. Yan, Z.; Qian, J.; Zhao, W. Discrimination Method for Water Inrush Source of Mine Based on Rough Sets Theory and BP Neural Network. In Proceedings of the 4th International Conference on Environmental Technology and Knowledge Transfer, Hefei, China, 24–25 May 2012; pp. 821–825.

97. Yang, Y.; Yue, J.; Li, J.; Yang, Z. Mine Water Inrush Sources Online Discrimination Model Using Fluorescence Spectrum and CNN. IEEE Access 2018, 6, 47828–47835.

98. Yang, Y.; Yue, J.-h.; Li, J.; Zhang, H.-r. Online Discrimination Model for Mine Water Inrush Source Based CNN and Fluorescence Spectrum. Spectrosc. Spectr. Anal. 2019, 39, 2425–2430.
99. Yang, Z.; Lv, H.; Xu, Z.; Wang, X. Source discrimination of mine water based on the random forest method. Sci. Rep. 2022, 12, 19568.
100. Zhou, M.; Dai, R. Study on Characteristic Raman Shift Screening Method Based on MPA for Raman Spectrum of Mine Water Inrush Source. Sci. Program. 2022, 2022, 5202265.
101. Donglin, D.; Luke, S.; Jinghua, M. Water inrush mode and countermeasures for Zhengzhou mining area. J. Min. Saf. Eng. 2010, 27, 363–369. (In Chinese)