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Application of artificial intelligence and machine learning in expert systems for the mining industry: modern methods and technologies

Natalya Mutovina, Margulan Nurtay, Alexey Kalinin, Aleksandr Tomilov, Nadezhda Tomilova
Information and Computing Systems Department, Faculty of Innovation Technologies, Abylkas Saginov Karaganda Technical University, Karaganda, Kazakhstan

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ABSTRACT

The mining industry has changed significantly in recent decades with the introduction of advanced technologies such as artificial intelligence (AI) and machine learning (ML). These innovations contribute to the creation of expert systems that help in optimizing processes, increasing the safety and sustainability of operations. This article is a literature review of modern AI and ML methods and technologies used in the mining industry. Discusses various intelligent and expert systems used to improve productivity, reduce operating costs, improve occupational safety, environmental sustainability, machine automation, predictive analytics, quality monitoring and control, and inventory and logistics management. The advantages and disadvantages of different approaches are analyzed, as well as their potential impact on the future of the mining industry. The review highlights the importance of integrating AI and ML into mining processes to achieve more efficient and safer solutions.

Corresponding Author:

Natalya Mutovina
Information and Computing Systems Department, Faculty of Innovation Technologies, Abylkas Saginov Karaganda Technical University
56 N. Nazarbayev av., Karaganda, Kazakhstan
Email: mutovina_natalya@mail.ru

1. INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) are pivotal technologies transforming numerous sectors, mining included. AI encompasses the realm of computer science focused on developing systems that can perform tasks traditionally requiring human intelligence, like speech recognition, decision-making, and problem-solving [1]–[3]. Machine learning, a subset of AI, specifically concentrates on devising algorithms that enable computers to learn from data and enhance their performance over time. The mining industry, as one of the oldest and most resource-intensive sectors, has always been in pursuit of new technologies capable of enhancing the efficiency and safety of mineral extraction. Machine learning has the potential to prevent or anticipate various incidents at industrial facilities [4]. The application of AI and ML in mining opens up new possibilities for addressing many challenges faced by mining companies [5]–[7]. The use of AI enables enhanced productivity, lower operational costs, improved workplace safety, and reduced environmental impact. The use of ML algorithms makes it possible to optimize the processes of mining and processing of minerals. For instance, ML-based systems can analyze mining data in real time, suggest optimal routes for mining equipment, and predict the most efficient mining methods [8], [9]. Predictive analytics based on ML improves the prediction of equipment breakdowns and plans its maintenance, which reduces the cost of repair and replacement of equipment. Such approach is especially important for large and expensive mining equipment [10]. AI and ML can analyze data from sensors and surveillance cameras to identify potentially dangerous situations and warn workers about possible accidents. For example, monitoring systems can monitor the condition of mines and predict collapses or methane emissions, which allows workers to be evacuated in a timely manner and precautions taken [11]–[13]. ML can also be used to monitor and manage environmental aspects of mining operations, such as air and water pollution control, waste management and land reclamation. It also reduces negative environmental impacts and complies with environmental regulations and standards. Leading mining companies are deploying autonomous vehicles and AI-driven drilling rigs, reducing the risk to human life and increasing mining efficiency. ML algorithms are used to analyze large volumes of data collected from sensors and equipment to predict potential equipment failures and plan preventive maintenance [14]–[16]. AI systems help monitor the quality of extracted raw materials in real time, analyzing samples and predicting possible deviations from the standard. ML allows optimization of supply chains and inventory management, which reduces costs and increases operational efficiency [17]–[20]. The application of AI and ML in the mining industry represents a significant step forward in the development of the industry as shown in Figure 1.

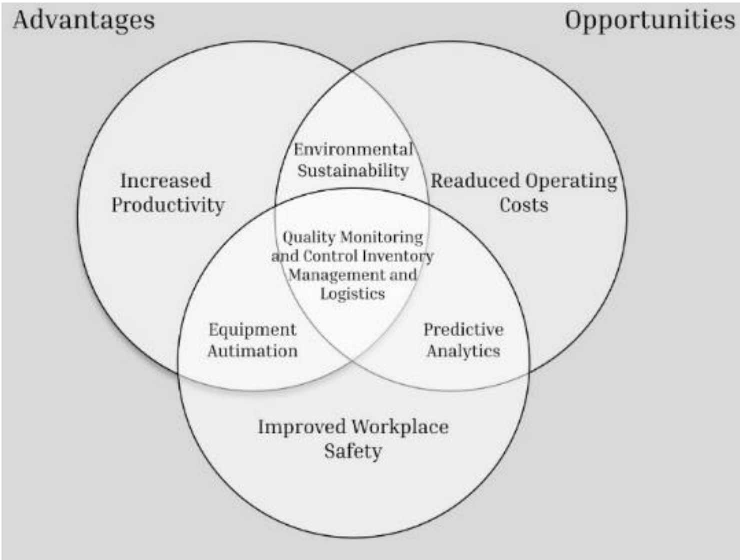

Figure 1. Advantages and opportunities of using AI and ML in the mining industry

These technologies not only increase productivity and reduce costs, but also significantly improve occupational reliability and minimize negative environmental impacts. With increasing demands for efficiency and sustainability, mining companies using AI and ML gain competitive advantages and open up new opportunities for further growth and development. This review will provide a comprehensive analysis of all aspects and potential problems that occur in the process of expert systems development to solve problems in the mining industry. A thorough analysis of existing studies on the application of artificial algorithms were used to solve specific practical issues in the mining industry. Since the authors' further goal is to develop Intelligence methods in mining will help identify the most relevant and priority areas for further development in this subject area. Through the review authors will analyze studies in which ML and deep learning an expert system for solving problems of mine workings support, special attention in the review should be paid to studies aimed at predicting and diagnosing various situations that arise during mining.

2. METHOD

2.1. The goal and objectives of the study

The main objective of this study is to provide a comprehensive review of the application of AI and ML in the mining industry, with a focus on expert systems. To achieve this goal, the following tasks were set:

Q1: Identification of the main directions and applications of AI and ML in the mining industry.

Q2: Analysis of existing expert systems, their advantages and disadvantages.

Q3: Identification of promising technologies and methods for the further development and implementation of AI and ML in mining processes.

This review aims to highlight both the theoretical advancements and practical applications of AI and ML in improving mining operations. By addressing these key questions, the study seeks to provide a critical analysis of the current state of AI and ML technologies in mining and their potential for future innovation. Furthermore, the findings will offer insights into how expert systems can be optimized for enhanced decision-making and operational efficiency in various mining environments.

2.2. Formulation of literature selection criteria

To conduct a qualitative literature review, the following selection criteria were identified:

a. Articles published in peer-reviewed journals and conferences.
b. Research conducted over the last 10 years to ensure data is up to date.
c. Works related to the use of AI and ML directly in the mining industry. Research containing empirical data, test results, and case studies of AI and ML.

In addition, preference was given to studies that provided a comparative analysis of different AI and ML methodologies employed in mining. Papers that addressed the obstacles and practical applications of implementing these technologies in real-world mining environments were also prioritized. Lastly, interdisciplinary research that combined AI, ML, and other fields s was included to capture a broader perspective on innovation in the mining industry.

2.3. Sources of information search

The following databases and resources were used to find for pertinent literature: Scopus, Web of Science, IEEE Xplore, and Google Scholar. Moreover, scientific journals and conference proceedings devoted to the use of AI and ML in the mining industry were analyzed. The search also included specialized mining engineering publications and industry reports to capture the latest advancements and practical applications of AI and ML in mining. In addition, case studies and technical papers from leading mining companies were reviewed to assess real-world implementations. This comprehensive approach ensured that the literature review covered both academic and industry perspectives on the application of AI and ML in mining industry.

2.4. Literature search and selection process

The literature search was conducted using keywords and phrases such as “AI in mining,” “ML in mining industry,” “expert systems in mining,” “AI applications in mining,” “ML in mining processes,” and others. All retrieved articles were pre-evaluated based on their abstracts and keywords to determine their relevance. After the initial screening, full-text articles were obtained for a more detailed evaluation of their methodologies and findings. The inclusion criteria also focused on the diversity of AI and ML applications across various stages of mining operations, such as exploration, extraction, processing, and safety monitoring. Studies that offered innovative approaches or proposed novel algorithms were particularly emphasized. Additionally, the geographical distribution of research was considered to ensure a global perspective on the adoption of AI and ML in mining. Finally, articles that provided knowledge about the future potential and difficulties of AI-driven technologies in the industry were prioritized for in-depth analysis.

2.5. Data analysis and classification

Data analysis and classification play a crucial role in understanding the diverse applications of AI and ML in the mining industry. By systematically categorizing the findings from the selected articles, valuable insights into the current trends and challenges faced in the field can be gained. All selected articles were analyzed and classified into the following categories:

a. Applications of AI and ML in different facets of the mining sector (*e.g.*, automation, predictive analytics, monitoring and quality control).
b. Types of expert systems and algorithms used (*e.g.*, neural networks, deep learning methods, decision support systems).
c. Advantages and disadvantages of applying AI and ML in mining processes.
d. Practical examples of implementation and results of using expert systems in the mining industry.

2.6. Synthesis and interpretation of results

Based on the analysis and classification of data, a synthesis of key findings and trends was conducted. The key areas where AI and ML show the most potential for application have been recognized, as well as the current problems and challenges that the mining industry faces when implementing these technologies. The synthesis revealed that AI and ML have the greatest potential in areas such as predictive maintenance, ore grade estimation, and optimizing drilling and blasting processes. However, challenges such as the lack of high-quality data, integration with existing systems, and high implementation costs remain significant barriers. The analysis also highlighted the need for more robust cybersecurity measures as AI systems become increasingly integrated into mining operations. Additionally, the importance of developing skilled personnel capable of managing and maintaining AI technologies was underscored. Upcoming studies should concentrate on overcoming these challenges to completely realize the capabilities of AI and ML in the mining industry. Furthermore, collaboration between academic institutions, industry stakeholders, and technology providers is essential to speed up the advancement and implementation of AI and ML technologies in the mining industry. Investment in research and innovation will be crucial for addressing both technical and practical challenges, enabling more efficient and sustainable mining practices in the future.

2.7. Discussion and formulation of recommendations

The final part of the review discusses the obtained results, draws conclusions about the current state of application of AI and ML in mining industry, and formulates recommendations for further research and practical implementation of expert systems. Special focus is given to the prospects for the development of technologies and their prospective influence on the future of the mining sector. The review emphasizes the need for continued advancements in AI algorithms, particularly in handling complex and unstructured mining data. Additionally, it highlights the importance of developing more scalable and cost-effective solutions to make AI and ML technologies accessible to mining companies of all sizes. The integration of AI with other emerging technologies, such as internet of things (IoT) and robotics, is identified as a critical area for future exploration. Furthermore, the review stresses the importance of regulatory frameworks and ethical guidelines to ensure responsible AI implementation in the mining sector.

3. LITERATURE REVIEW

This review analyzes the leading studies using AI methods in the mining industry. Applications of ML, including regression analysis, clustering, and classification, to predict ore grade and optimize production processes are discussed. Convolutional neural networks, which are used to analyze rock samples, and recurrent neural networks, which are used for time series anticipating in the mining industry, are highlighted as shown in Figure 2. Each study is analyzed in relation to its positive sides and drawbacks. Benefits include increased forecasting accuracy and improved resource management thanks to the capacity to identify various trends and dependencies of information base. However, disadvantages include difficulty in interpreting results, high computational requirements, and the requirement for substantial data to train models. This review seeks to offer a comprehensive summary of recent developments in the usage of intelligent systems in mining industry, highlight the potential and difficulties of each of the reviewed techniques, and contribute to the further development of this important area of science and technology.

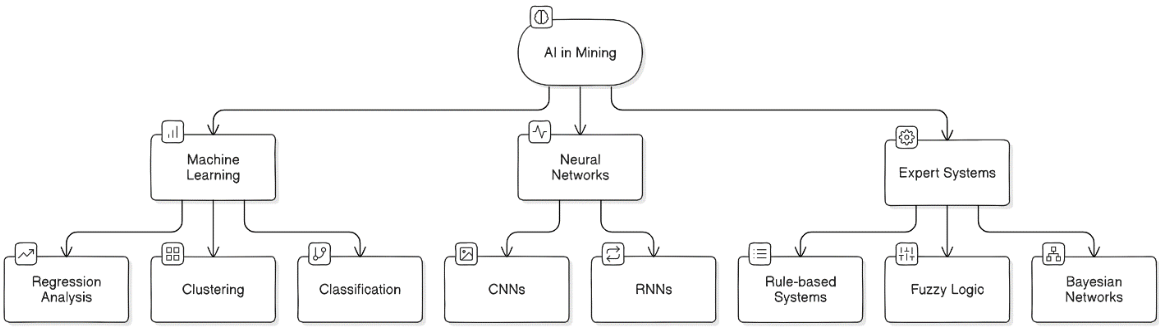

Figure 2. Directions of AI in mining

3.1. Classical machine learning models

This paper uses ML to forecast bolt failures in a mining environment. The advantages include the ability to analyze real data from underground mines. The authors applied different variations of the support vector machines (SVM) model such as principal components analysis (PCA-SVM) and gradient tree boosting (GTB-SVM) to assess the failure risk of bolt supports in underground coal mines. The PCA-SVM model stands out and showed significant advantages over the other two approaches. By applying PCA-SVM, the authors were able to solve the problem of multicollinearity of features and select only the most important ones, as well as achieve an area under the ROC curve (AUC) score of 0.85 on the training set and an AUC score of 0.86 on the test set. The GTB model also reduced the number of features, but its AUC was 0.82 on the training set and 0.81 on the test set, indicating a significant loss of data following feature extraction. The utilized dataset in the study includes both continuous data and discrete spatial data. Additionally, the outcomes revealed that PCA, as a feature conversion method, allows for better extraction of complex data compared to the feature selection method. The authors also noted that their future work will be aimed at testing nonlinear feature transformation methods, such as autoencoders, as well as more complex datasets [21].

The authors considered premature failure of rock bolts in underground mines. It is becoming a major critical issue due to the complex mechanisms and multiple influencing factors, which makes laboratory predictions often unreliable. The study addresses this issue by application of the categorical gradient boosting (CatBoost) algorithm and Shapley additive explanations (SHAP) to predict rock bolt failures with high accuracy and transparency. Using a dataset from an underground coal mine, the CatBoost algorithm demonstrated excellent prediction capabilities, with high AUC values and better performance than Random Forest. The SHAP analysis showed that "roadway length" is the main factor contributing to rock bolt failure, with increasing risks in roadways longer than 30 meters and in the presence of high-sulfur groundwater. Rock bolts younger than five years were found to be significantly less susceptible to failure. The study demonstrates valuable understanding of the intricate relationships between rock bolt failures and various geotechnical and ecological variables, highlighting the importance of explainable ML to improve safety and reliability in underground mining. Thus, this study illuminates the complex relationships between rock bolt failures and the impact of geotechnical and environmental variables. The proposed approach has clarity and interpretability, which can facilitate the implementation of transparent ML for rock bolt failure risk evaluation in subterranean mining operations [22].

This review presents the current state of the art in applying ML to stress corrosion cracking risk assessment. There are many forms of corrosion, some of which carry minor risks while others can lead to catastrophic failures of engineering materials. Stress corrosion cracking (SCC) is a highly severe form of corrosion that is challenging to detect. It results from crack propagation in a corrosive environment combined with the application of tensile stress to metals or alloys. Predicting and identifying SCC occurrences remains a critical challenge for corrosion scientists and engineers [22]. The progression of technology and the fourth industrial revolution have led to an unprecedented increase in available data. Leveraging this data to address real-world challenges has gained significant attention in recent years. The accessibility of this data enables AI and ML to serve as advanced technologies for tackling complex issues and uncovering insights that would otherwise be unattainable. ML is particularly useful in corrosion prediction applications, allowing the use of corrosion-influencing data such as environmental parameters (temperature and humidity), process conditions (flow circumstances, flow temperature and pressure), material characteristics (material type, material thickness, process device dimensions), existing corrosion protection measures, and visual conditions [22]. All these data can be utilized in ML algorithms to model and predict the occurrence of stress corrosion cracking and conduct risk assessments. This paper attempts to review the available research on the application of ML to SCC. It also presents the current advances in ML and SCC, identifies current gaps in knowledge, as well as outlines potential avenues for future research in the field of deterioration risk assessment using ML [23].

This study aims to quickly and accurately predict gas explosions in coal mines using the real-time data gathered by the smart system of mining, covering monitoring of mining safety, worker tracking, and visual monitoring systems. Initially, the mine accident prevention software has divided on subsystems considering accident contributing factors, surrounding conditions and vulnerable objects, which can establish a proactive warning system to predict gas levels explosions. Therefore, a dataset to train is chosen arbitrarily beginning from the identified coal mine samples, which is analyzed and processed using MATLAB software. Next, a learning algorithm formed from the bagging classification algorithm (Kopeć *et al.*) is built, which is enhanced using the parameters Mtry and Ntree. As a result of comparing the built model with the support vector machine classification model, special coal mine cases are carried out to validate the effectiveness of the improved gas explosion warning algorithm. The practical outcomes reveal that the improved bagging classification algorithm achieves 100% accuracy in forecasting results in coal mines, while the precision metrics of the SVM model is only 75%. The improved algorithm also demonstrates reduced model deviation and proportional error, confirming its superior performance in early detection systems for coal mine gas explosions. The advantages of this approach include high prediction indicator and dependability of the warning system, capability to operate in real-time, and the use of multivariate data analysis to improve safety management in coal mines. However, the study has limitations, including the limited number of study samples and only focusing on the prevention of gas explosions, not covering other potential risks such as fires and geological disasters [24].

Mining activities lead to adverse environmental impacts, and such regions demand continuous observation, which can be done using remote monitored data. The paper examines the effects of subterranean coal extraction in one mine of Poland. Spectral indices, satellite-based radar interferometry, geographic information system (GIS) tools and ML algorithms were employed. A spatial model was created that determines the statistical importance of the impact of various elements on the emergence of swamps. The findings demonstrated that changes in the normalized difference vegetation index, terrain elevation, water table level and surface deformation significantly affect the emergence of wetlands. The model based on the random forest (RF) classifier effectively identified potential flood zones with an accuracy of 76%. Geographically weighted regression (GWR) analysis allowed us to identify local anomalies in the influence of the chosen variables in the formation of swamps, which contributed to understanding the reasons for their development. The use of RF and GWR allowed us to obtain accurate and detailed data on the influence of various factors on the formation of wetlands. The study takes into account various parameters (optical, radar, geological, hydrological and meteorological data), which allows us to obtain a comprehensive understanding of the problem. The use of available remote sensing data makes the methodology accessible and cost-effective for widespread use. The model can sometimes incorrectly classify flood zones, which requires additional data filtering efforts. The score of ML models is strongly reliant on the quality and volume of available dataset, which may limit their use in some regions. To enhance the model precision, it is essential to utilize more accurate geological and hydrological data, as well as expand the model with additional variables, which can complicate the analysis process [25]. Coal and gas emissions are one of the major factors contributing to fatalities in underground coal mines and associated risks to coal-fired operations global energy producing from coal. Currently, methods such as tracking methane concentrations with sensors, conducting geophysical investigations to detect geological formations and emission-prone zones, and empirical modeling to predict emissions are used to prevent them. However, with the development of industry 4.0 advances, numerous examinations have explored the use of AI methods for forecasting emissions. The proposed approaches and their outcomes show considerable variation in the publications. The research [26] examines how ML is used to forecast coal and gas emissions in subterranean mines employing a hybrid method. The majority part of the found works focusing on prediction of the coal and gas emissions using ML was reviewed in China [26].

The results show that authors trained various ML models, mainly combining them with various optimization techniques, incorporating analysis of particle swarm, genetic algorithms, the theory of rough sets, and inverted algorithm of fly optimization to forecast the emission. The quantity and kind of input variables for forecasting varied substantially, where the initial gas velocity is the most significant variable to find gas emissions and depth of the coal seam being the most significant argument of coal emissions. The training and testing set of the models proposed in the literature showed significant variation, yet they were inadequate in most cases, which casts doubt on the dependability of certain applied models. Upcoming studies will explore how data size and input parameters influence the forecasting of coal and gas emissions. The advantages of applying ML methods to emission forecasting include the capacity to handle huge datasets and automatically enhance models as new data becomes available, enhancing the precision and dependability of forecasts. Such disadvantages include the reliance on the quality and quantity of input data, and the need for complex model tuning to obtain reliable results.

3.2. Deep neural networks

A smart identification and localization system method for steel belt anchor hole in underground coal mine was proposed based on the improved you only look once version 5 (YOLOv5) model. The main advantages of this approach include the improved detection accuracy of anchor holes by using super-resolution (SR) methods to enhance image clarity and implementing the coordinate attention (CA) module into the YOLOv5s backbone network. This model is capable of accurately detecting the characteristics of small target objects, and improve the detection success rate. In addition, the SR-CA-YOLOv5s model achieves high average detection accuracy (96.8%) and is capable of real-time operation while maintaining a high processing speed (166.7 fps), which meets the requirements for responsiveness. Thus, SR-CA-YOLOv5s is a modified version of YOLOv5s with a CA mechanism and likely additional SR optimization to improve the performance of the model and accuracy in image processing. However, disadvantages of model include a decrease in the frame rate of 18.5 fps and the need for high-performance computing to train and operate the model in an underground mine environment [27].

This paper outlines the findings of research on how a method based on artificial neural network have been applied to simulate the tunnel boring machine (TBM) advancement rate. The advancement rate of a TBM in rock conditions is an essential factor for the successful completion of a tunnel construction project. A database was created including the real TBM advancement indicators, single-axis compressive strength of rock, spacing between planes of flaws in the masses of rocks and the rock quality index. The data were gathered from three distinct TBM projects. An optimal architecture was determined to be a five-layer neural network with three neurons in the input layer, 9, 7, and 3 neurons in the first, second, and third hidden layers respectively, and a single neuron in the output layer. The correlation has been calculated for the advancement rate forecasted by artificial neural network was sufficiently high. The correlation coefficient of 0.94 indicates a high accuracy of TBM advancement indicator predictions that is capable to significantly improve project planning and implementation. The model was trained on data from three different projects, which increases its applicability in different geological conditions. The study allowed us to determine the optimal structure of the neural network for this task, which improves its performance and reliability. As a drawback, we noted the dependence on data quality; the model requires high-quality and representative information, which can be complex to provide. Tuning and optimizing the neural network parameters require significant computing resources and specialized knowledge. The model may be less effective when used on projects with geological conditions that are very different from those on which it was trained. Thus, the utilization of the deep learning methods for TBM penetration rate modeling offers significant advantages in terms of accuracy and optimization, but requires taking into account the limitations associated with data quality and the complexity of model tuning [28].

In this paper, the anticipation of rock-caused stress during pillar extraction is investigated using ML methods [29]. The models take into account factors such as working depth (H), panel width/length (W/L), pillar width/work height (w/h), goaf length, and extraction area [29]. The paper emphasizes the significance of operational parameters in comparison to geological ones. In the cases analyzed, the correlation coefficient for rock-induced stress is approximately 80% for the RF model and about 76% for the multilayer perceptron (MLP), demonstrating the superior performance of the RF model. The developed models predict the stress conditions of pillars. Despite many advantages, ML also has its drawbacks. ML models require training on historical data to obtain accurate predictions, and the algorithm's precision relies on the quantity and dependability in this dataset. However, ML has limited to be applied only to specific areas, and additional training of the model is required to work with new data. In this study, only four panels of continuous miners are analyzed, considering the limitations of data collection and the limitations from one coal mine. Going forward, additional panels and varied geo-mining conditions can be considered to improve the model. Therefore, stress prediction in subsurface coal mines remains as the most important obstacles for mining engineers, despite automation, advanced tools, and numerical modeling methods [29].

Effective forecasting ground vibrations resulting from blasting in opencast mining plays a significant role in minimizing environmental grievances. This study proposes a new hybrid evolutionary artificial neural network (ANN) optimized using a genetic algorithm (GA) for predicting peak particle velocity (PPV). The optimized GA-ANN model automatically selects the optimal ANN architecture including the quantity of neural units, functions of activation, learning algorithm and the number of epochs. The dataset, comprising maximum charge mass per delay, horizontal distance (HD), radial distance (RD), and a newly modified radial distance (MRD) between the monitoring and blasting stations, was utilized to evaluate the proposed method at the Sungun copper mine in Iran. A performance evaluation of the GA-ANN model using statistical indicators demonstrates its superiority over empirical prediction methods and the neuro-fuzzy inference system. A significant result is that using modified radial distance (MRD) instead of traditional HD and RD distances improves the prediction accuracy. In summary, the results demonstrate the effectiveness of the proposed GA-ANN method for identifying the optimal ANN architecture for PPV forecasting. The advantages of using the novel hybrid evolutionary ANN are: increased forecasting accuracy due to the use of MRD, optimization of the ANN architecture using GA provides higher model performance, and a systematic and automated approach to selecting ANN parameters. The disadvantages noted are: a substantial volume of data for model to achieve high accuracy, the model may be limited by the specificity of the application domain and not adapt to new conditions without additional training, a limited amount of data and tests may affect the ability of the model to generalize and its real-world applicability to other mining developments [30].

An attempt was made to estimate and forecast blast-induced ground vibrations and frequencies based on rock variables, modeling of blasts and explosive parameters through an artificial neural network. A three-layer, feed-forward, back-propagation neural network with 15 hidden units, 10 input variables, and two output variables was developed using 154 experimental and monitoring blast data from a large surface coal mine in India. Twenty new blast datasets were utilized to validate and compare the prediction of peak particle velocity and frequency using ANN and other forecasting methods. To enhance reliability in the suggested approach, the same datasets were employed to predict PPV using both established vibration predictors and multivariate regression analysis. The outcomes were evaluated by comparing the correlation and mean absolute error between the observed and forecasted PPV and frequency indicators. The ANN results showed a very close match with the experimental data, indicating high accuracy in contrast to traditional anticipators and multivariate regression analysis (MVRA). ANN has the ability to recognize new patterns that were not previously presented in the train part and refresh its understanding over time when new training data is added. As a disadvantage, it is noted that the development and tuning of ANN requires significant computational resources and specialized knowledge to optimize the network architecture. Although ANN takes into account more parameters than traditional predictors, it may still not take into account all possible influencing factors, which may limit the accuracy of forecasts in some cases [31].

This study focuses on the application of methods, namely bagging models and one-layer neural network, to forecast stress conditions caused by mining activities of Indian subsurface coal excavations. Focus is on predicting the behavior of strata in mining zones where the cobblestone and pillar method is used. The study revealed that operational parameters such as working depth, panel width and length, pillar width and working height, corrugation length and mining area play a key role in the models built to predict mining induced stress. As opposed to geological factors, operational parameters were found to be more important for the accuracy of predictions. The developed models exhibited high correlation coefficient (R2) reaching 85% for bagging model and 76% for one-layer neural network, indicating their effectiveness in predicting pillar stress conditions under different operating conditions. These findings help managers to take proactive measures to minimize risks in the coal industry including developing emergency response plans. The study also found that RF demonstrated higher accuracy compared to MLP, although the latter showed a higher mean absolute error. In the realm of subsurface coal mining, the application of ML tools is innovative and can significantly improve the safety and efficiency of processes. Future research can be aimed at improving the models, as well as exploring other computational techniques, such as the finite element way and finite difference approach, which will allow for more in-depth and accurate predictions of rock behavior under different operating conditions. Thus, while the application of AI and ML techniques of structural health monitoring offers significant benefits, it is important to consider their limitations to develop effective and reliable damage detection systems [32].

This study focuses on the use of explosives as a power source for breaking rock material. Most of the blast power is misplaced as earthquakes, noise, air bursts, and other factors. Earthquakes caused by blasts depend on numerous elements including rock mass composition, explosive properties, and blast planning. Forecasting of blast-induced earthquakes though regression methods is at times, overly cautious, which creates obstacles for efficient and safe mine operation. The scaled distance approach remains a reliable method for predicting vibrations, however, there are other alternative methods that show similar outcomes with strong correlation coefficients [33].

Contemporary analysis and anticipation tools such as ANN have demonstrated to be an outstanding method of vibration prediction, as confirmed by many researchers in their work. Another method used in the study is an ensemble learning method such as RF, which builds multiple decision trees and shows good results in both classification and regression. The work makes an effort was made to forecast maximum fragment velocities in explosions at different distances using the RF, ANN and scaled regression methods. Each method, correlation coefficients were obtained using different initiation systems, which revealed that ANN demonstrates the highest values of correlation coefficients, showing the most accurate results among the three considered methods. RF also showed good results, although lower compared to ANN, but superior to the scaled regression methods.

The authors made the following useful conclusions:

a. Out of the three methods utilized to predict blast-induced vibrations, ANN anticipated the most reliable values of the biggest correlation indicators. This makes ANN the preferred tool to anticipate blast-induced oscillations in mining.
b. The strongest correlation indicator values for all of these approaches were achieved using the electronic initiation system. This demonstrates the accuracy of such a system, which contributes to a more accurate prediction of vibrations caused by explosions.
c. Based on the conducted study, it can be concluded that it is recommended to use electronic detonators with the predictive ANN model to accurately predict the vibrations caused by blasts in controlled blasting operations to calculate the peak value in regulated blasting operations, instead of the bagging model and scaled regression methods. This can greatly help mine operators when conducting controlled blasting operations near populated areas.

The paper explores how deep learning is used to detect open-pit mining operations using space imagery, treating it as a land utilization and land cover classification problem. Using convolutional neural networks (CNN) and pre-trained visual geometry group (VGG), residual network (ResNet) and densely connected convolutional networks (DenseNet) architectures, a huge train data of “coal mine” images and a large number of “non-coal mine” images was prepared. The VGG model using transfer learning achieved the highest model precision of approximately 100% on the validation set. These results indicate high accuracy and the potential for applying model to detect coal operations in different countries. The model showed 98% accuracy on the validation dataset and more than 95% on test images from other countries, which demonstrates its reliability. Using CNN can greatly simplify the process of monitoring and detecting coal mines compared to traditional methods. The model can be updated and improved with new data, allowing it to remain relevant and effective. We would like to note that the model is prone to false positives, which can lead to additional work to filter out incorrect data. The model may misclassify other types of mines, such as copper, which requires additional data preprocessing measures [34].

As a fundamental component of AI, ML offers substantial benefits in multi-criteria intelligent assessment and decision-making. The degree of maintainable progress is of crucial role in evaluating the safety of coal mining companies. At this work, the Backpropagation neural network approach is employed to make solutions on the indicator of maintainable development and assess the safety of coal mining enterprises. Drawing from the research of methods for assessing the sustainable development of coal companies, a system of evaluation indices is created and a multilayer forward neural network is built based on the backpropagation algorithm. According to the human-machine-environment-control system theory and taking the four individual elements and the entire coal operations system as the subject of the research, a system analysis and examination has been done to assess and simultaneously enhance the internal reliability of mines [35].

The benefits of backpropagation neural network are that it avoids subjectivity and complex mathematics of traditional estimation approaches, and it is capable to produce steady and accurate outcomes even in the presence of some incomplete data and argument deviation. Backpropagation provides research-based and conceptual instruction for decision-making on continuous advancement for coal mining companies and has some scientific assessment. The disadvantages of method are the dependence on the quality of the initial data and the need to fine-tune the model to achieve high accuracy. Progressive study will concentrate on such areas as enhancing the proposed algorithm's analyzing efficiency and accuracy, and leveraging big data technologies to analyze text data collected during coal mine operations to strengthen the predictive control of workplace safety risks in coal mines. The objective of coal suppliers is to provide a substantial volume of coal of the necessary level with minimal costs for its extraction. Subsequently, predicting power characteristics is one of the most crucial tasks aimed at optimal use of the energy indicator. The goal of the authors' work is to find, investigate, and assess the most capable AI algorithms extensively adopted in the mining industry in practical applications prediction problem. The research was conducted using data collected from laboratory conditions over a period of five years (2005-2010), including 33,256 coal samples from the Kreka Coal Mine company. It was aimed at building a prediction model based on the described data, which will be utilized to predict the quality category of uncertain coal units. As part of the work, four algorithms were determined: C4.5, k-nearest neighbor (KNN), naive Bayes (NB) and MLP [36].

The goal was to identify the optimal model by following these steps: each algorithm is tuned to identify appropriate model partitioning methods that enhance algorithm precision, the significance of input features is evaluated, and finally, the algorithms are compared based on their effectiveness The final evaluation of the results identified MLP as the best forecasting method for this field with an ideal configuration for the input, hidden, and output layers. The predictive model for the field was attained the optimal composition (14-24-7) for all of the network layers. The outcomes show that the model can be a crucial instrument for forecasting coal quality. New insights can serve as a crucial support to make a decision and control the different systems, assuring product and production quality. For upcoming research, it is planned to study the possibility of introducing the resulting predictive model into an online observing system of the real indicators of the material of coal moving along the conveyor, which will provide information about the quality of coal in real time. This study highlights the critical vulnerability of coal mines due to insufficient air flow, which poses significant risks to reliability and personnel management. Therefore, ongoing surveillance of air flow in underground mines is essential to detect potential disasters. Various AI methods are used to estimate nonlinear air flow parameters in mines, but often encounter problems such as local minima and poor convergence speed [37]. Semin and Kormshchikov [37] proposes a new model that combines adaptive neuro-fuzzy interface system (ANFIS) with GA to forecast power usage as well as air flow in underground mine ventilation systems. GA is used to automate the discovery and configuration of network architectures, reducing the need to manually configure optimal network design. As a comparison, two predictive benchmark models, particle swarm optimization and Bayes optimization (BO), are presented to illustrate the effectiveness of GA in detecting the best hyperparameters for ANFIS and ANN models. Experimental analysis validates the proposed model against several baseline approaches using statistical parameters such as root mean square error, mean absolute error, and coefficient of determination (R square). The findings reveal outperformance of the developed model against baseline models on these performance metrics. Thus, this work advances ventilation and monitoring technologies in mines with the goal of improving operational reliability, improving safety and health conditions, reducing energy and operating costs, and increasing overall mine productivity. This study also demonstrates a distinctive hybrid neuro-genetic system (ANFIS-GA) to optimizing algorithm structures, which not only reduces computation time and cost, but also leverages the capability of GA to produce more optimized model structures.

3.3. Recurrent neural networks

The authors of suggested solution based on unified manifold approximation and projection (UMAP) and long short-term memory (LSTM) methods to forecast fire conditions in sealed zones of underground coal operations. This model protects the lives of miners by providing early warning of impending dangers. The suggested predictive model visually presents the fire conditions in the format of an Ellicott expansion plot.

Effectiveness of the suggested forecasting model is experimentally measured in contrast of current models such as support vector machine (SVR) and autoregressive integrated moving average (ARIMA). It was observed that the UMAP-LSTM model demonstrated the lowest root mean square error in predicting gas concentrations across various types, indicating a higher efficiency of the proposed forecasting models. Fires in mines frequently result in explosions caused by gas and coal dust, which pose a danger to the lives of miners and complicate rescue efforts. Therefore, it is necessary to monitor the state of the gas mixture in sealed areas and study trends in the explosiveness of the gas mixture over time. Knowledge of future gas concentrations allows immediate action to be taken to eliminate the hazard [38].

This study introduces a deep neural network designed to predict gas concentrations in sealed sections of underground coal mines, utilizing various IoT sensors placed in a metal gas reservoir. Air is automatically drawn from the sealed area at set periods using a solenoid valve, suction pump, and programmable microcontroller. Gas level meters continuously observe the gas levels within the coal operation and relay the density data to a server room on the surface via a wireless network, with cloud data storage for further processing. In this study, a forecasting model is proposed that combines dimensionality reduction techniques with recurrent models capable of retaining memory, aiming to improve prediction accuracy. The t-SNE model method is used to reduce the complexity of recorded gas concentration data, while the VAE layer reconstructs the internal features of the low-dimensional gas concentrations. The Bi-LSTM layer is then employed to predict the concentrations of gases. The advantages of suggested recurrent model for predicting gas concentrations in sealed areas of coal mines include high prediction accuracy, as evidenced by low mean square error (MSE) values compared to alternative auto regressive integrated moving average (ARIMA) and chaos time series (CHAOS) models. The model is able to effectively account for the complex relationships between the concentrations of various gases and time, which makes it more adaptive to changes in the mine environment. In addition, the use of t-distributed stochastic neighbor embedding (t-SNE) and variational auto encoder (VAE) technologies can reduce data dimensionality and extract important features, which enhance the overall productivity of the solution. However, the model also has disadvantages. Particularly, the complexity of setting up and interpreting the results can be high due to the use of several complex algorithms (t-SNE, VAE, and bi-LSTM) that require deep understanding and experience in ML and geology. In addition, the model requires significant computational resources and training time due to its deep architecture and the need to process large amounts of data [39].

Early detection of cracks allows for prompt action to address them, guaranteeing the reliability of both workers and machinery in surface coal operations. Observation of cracks in these areas is crucial for safeguarding workers and protecting national resources. Digital twins (DTs) are essential for fracture identification in surface coal mines, offering continuous, real-time observing of mine conditions and the adjacent area. Multiple sensors and IoT tools collect ground motion and stress data. Integrating this data into DT allows the identification and analysis of anomalies that could signal the development or spread of cracks. This work proposes a deep neural network with dense connectivity and low weight embedded in DT for fracture identification and proactive maintenance decision making via integrating time series, live data collected from sensors, and information from forecasting models. The proposed DT system is capable to predict the form of cracks, which allows proactive measures to eliminate them. When comparing the performance of the network with other models, it was found to surpass all cutting-edge deep neural networks in several key metrics, including accuracy, recall, precision, average accuracy, F1-measure. The model demonstrated superior performance in average accuracy and surpassed several detection models and recurrent neural networks in both training and prediction times. The advantages of the proposed system lie in its holistic approach to crack detection, which combines live observation, forecasting analysis, modeling, visualizing, and solution maintenance. This integration enables specialists in mining sector to enforce the reliability, improve sustainable activities, moreover, to reduce the bottlenecks related to cracks and structural vulnerability. Disadvantages of the system may include difficulty in setting up and the need for a large amount of data to ensure high accuracy and reliability of forecasts [40].

4. DEVELOPMENT OF AI AND ML IN THE MINING INDUSTRY

To advance the development and application of AI and ML in mining operations, it is essential to identify promising technologies and methods. Mastering these technologies and methods can significantly improve various aspects of mining processes. As a result, they can greatly enhance the efficiency, safety, and sustainability of mining operations.

One of the key areas is the use of IoT [41] and intelligent sensors for tracking various parameters of mining operations. Smart sensors can collect data on vibrations, temperature, pressure, gas content and other critical indicators. Integration of this data with AI [42] and ML systems will allow you to quickly analyze the condition [43] of equipment and infrastructure, predict possible breakdowns and take preventive measures as shown in Figure 3 [44].

Cloud technologies offer robust resources for storing and processing large volumes of data gathered through IoT devices as well as various resources [45]. Big data analysis using ML methods allows you to identify hidden patterns and trends, which helps optimize production processes, manage risks and reduce operating costs [46]. Augmented and virtual reality technologies can be used for personnel training, planning and modeling of mining operations [47]. With their help, you can create virtual simulations that allow you to train workers without risking their life and health, as well as plan complex operations taking into account all possible scenarios [48].

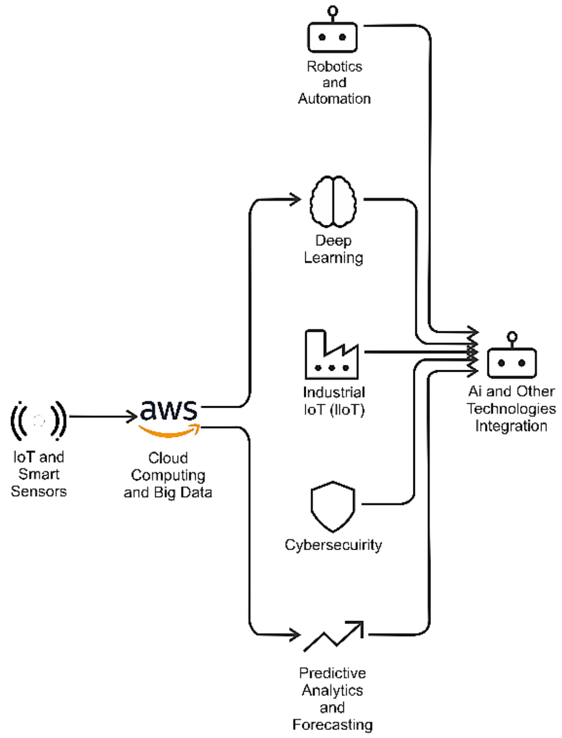

Figure 3. Promising technologies and methods for the further development and implementation of AI and ML in the mining industry [49], [50]

Robotization and automation of mining processes can significantly improve their efficiency and safety. Modern robotic systems are capable of performing complex tasks in conditions that are dangerous to humans. The introduction of autonomous robots and unmanned aerial vehicles (UAVs) [51] for exploration, drilling, transportation and other operations reduces the risk of human errors and increases productivity. Deep learning techniques demonstrate significant effectiveness in analyzing complex and diverse data. The application of deep neural networks for processing geological data, predict mineral content, and optimize mining and processing processes can significantly improve the results of mining operations [52].

The industrial internet of things (IIoT) [53], [54] combines all of the above technologies, creating a single ecosystem for managing production processes. IIoT allows the integration of data from various sensors and devices [55]–[58], providing centralized control and management of all aspects of mining operations. As digital technology advances in the mining industry, the need for cybersecurity increases. Robust systems to protect data and infrastructure from cyberattacks are a key component for successful implementation of AI and ML. Developing and implementing advanced cybersecurity practices will protect critical data and ensure the smooth operation of all systems. Using predictive analytics and ML-based forecasting techniques, you can predict potential problems and optimize production processes. This includes forecasting equipment wear and tear, inventory management, maintenance planning and other aspects that help reduce costs and improve efficiency [59]. Combining AI with other advanced technologies such as blockchain can provide additional transparency and security in supply chain and document management. Blockchain allows you to securely record and track all transactions and operations, which is especially important for logistics and inventory management in the mining industry. Identifying and implementing these promising technologies and methods requires an integrated approach and close collaboration between research institutions, mining companies and technology developers. Funding for research, development, education, and skill development, will support the wider and more effective use of AI and ML in the mining industry. This, consequently, will result in higher productivity, lower costs, and enhanced safety and sustainability of mining operations [60], [61].

5. PROBLEMS OF ARTIFICIAL INTELLIGENCE APPLICATION IN THE MINING INDUSTRY AND FUTURE RESEARCH DIRECTIONS

The use of AI and ML in the mining industry has the capacity to transform operations by enhancing efficiency, safety, and productivity. Nonetheless, the incorporation of these advanced technologies comes with its own set of challenges. This section outlines the primary problems associated with AI and ML application in the mining industry and suggests future research directions to address these issues.

5.1. Problems of AI application in the mining industry

One of the main challenges in applying AI and ML in the mining industry is the quality and availability of data. Mining operations generate the sufficient amount of information, however, often this information is unstructured, incomplete, or noisy. Inconsistent data collection methods and the lack of standardized data formats can further complicate the analysis. High-quality, clean, and well-labeled data is essential for training accurate and reliable AI models. Mining operations frequently depend on outdated systems that were not built to integrate with contemporary AI technologies. Integrating AI solutions with these existing systems can be complex and costly. There is a need for seamless integration methods that allow AI to work alongside traditional mining equipment and software without extensive modifications. Implementing AI in mining requires specialized skills that are often lacking in the industry. There is a significant gap in the workforce's knowledge and expertise in AI and ML, which can hinder the adoption of these technologies. Training existing personnel and attracting new talent with the necessary skills is crucial for successful AI implementation. The deployment of AI technologies involves a substantial initial investment in terms of both capital and resources. This includes costs associated with purchasing advanced hardware, developing custom AI solutions, and ongoing maintenance and support. For many mining companies, especially smaller ones, these costs can be prohibitive. Mining operations are often targeted by cyber-attacks due to the valuable data and resources they handle. Implementing AI systems can introduce new security vulnerabilities, making it imperative to ensure robust cybersecurity measures. Additionally, the collection and analysis of information trigger privacy issues that must be resolved to protect sensitive information. The implementation of AI in mining brings up regulatory and ethical concerns. Compliance with local and international regulations governing data usage, environmental impact, and worker safety must be ensured. Furthermore, ethical considerations regarding the impact of AI on employment and the environment need to be carefully managed.

5.2. Future research directions

Future studies should concentrate on creating more advanced data processing techniques to handle unstructured and noisy data. This includes the creation of algorithms for data cleaning, normalization, and integration from multiple sources. Improved data processing will enhance the quality and reliability of AI models. Establishing interoperability standards for AI systems in mining is essential for seamless integration with legacy systems. Research should aim to develop frameworks and protocols that facilitate the interoperability of AI technologies with existing mining infrastructure.

Research initiatives should explore effective methods for training and upskilling the mining workforce in AI and ML. This includes developing specialized training programs, online courses, and collaborations within the industry to address the skill gap and promote a culture of ongoing learning. Future research should focus on creating cost-effective AI solutions that can be adopted by mining companies of all sizes. This involves the development of scalable and modular AI systems that require lower upfront investment and offer flexible payment models such as AI-as-a-service (AIaaS). As AI systems become more integrated into mining operations, research should prioritize the development of advanced cybersecurity measures. This includes the creation of AI-driven security tools to detect and mitigate cyber threats in real-time, ensuring the protection of critical data and infrastructure. Research should also focus on the ethical and regulatory issues related to the use of AI in mining. This includes developing comprehensive guidelines and frameworks that ensure compliance with legal requirements and promote ethical AI usage, balancing technological advancement with societal impact. Another promising area is reinforcement learning. For example, in study [62], RL algorithms are used to optimize the operation of unmanned speed control of mining electric locomotives utilizing slip control technology on various vehicles, which allows increasing productivity and reducing energy costs. The study [63] built a deep RL system for mineral prospectivity mapping using the example of gold prospectivity mapping in northwestern Hubei Province, China. The ability of reinforcement learning models to adapt to different conditions during the learning process allows one to achieve better results in solving various problems and implement complex intelligent systems.

The application of AI and ML in the mining industry has already proven effective, but many technologies are at an early stage of adoption. One of the key challenges is dealing with unstructured and noisy data, making it difficult to create high-quality AI models. While algorithms for data cleaning and normalization are showing progress, questions remain regarding data accuracy and reliability. For example, combining data from various resources is often challenging, such as heterogeneous data formats and incompleteness. This affects the final quality of the models, which requires further improvements. Another important aspect is the interoperability of AI systems with existing mining infrastructures. Despite active research in this direction, the development of standards and protocols that enable seamless integration remains an important challenge. Without standardized approaches to integrating AI with legacy systems, the effectiveness of technology adoption will be limited.

Currently, various AI and ML approaches have been applied in the mining industry, including deep learning algorithms, support vector machines, and reinforcement learning (RL). For example, in the study [62], reinforcement learning is successfully applied to optimize the control of mining electric locomotives, which reduces energy costs and increases productivity. While deep learning performs well in prediction and pattern recognition tasks, RL adapts to dynamic conditions more efficiently, making it preferable in tasks with high demands for changing operating conditions. The industry's implications involve higher productivity, lower operational expenses, and enhanced safety standards in the workplace. However, without proper data management and quality data processing, the potential benefits of AI may be limited. Further research should focus on building more resilient data processing systems that will provide more accurate predictions and automate complex tasks.

Looking ahead for the mining sector, it is important to develop affordable and scalable AI solutions that can be implemented by both large and small enterprises. Developing cost-effective solutions, such as AIaaS, will lower the barriers to entry for companies with fewer resources and allow for wider adoption of AI in the industry. The development and creation of better algorithms for data cleaning and integration will improve the quality and reliability of AI systems being developed. It is also necessary to continue developing protocols and standards to simplify the integration of AI systems with existing infrastructures.

6. RESULTS AND DISCUSSION

This research has confirmed that the application of AI and ML in the mining sector can significantly increase productivity, enhance reliability, and decrease operating prices. Particularly, AI and ML technologies have been successfully applied in predictive analytics, machine automation and inventory management. We also identified areas in which these technologies are helping to increase resilience, such as improved quality control and monitoring. The results of the study supported the hypothesis that AI and ML have the potential to address the mining industry's current challenges related to reliability as well as efficiency. In response to objective Q1, the review highlights how AI and ML can be essential instruments for enhancing efficiency and reliability in the mining sector. Various studies have shown positive results when using AI and ML in areas such as predictive analytics, inventory monitoring and management, and machine automation. However, it is also crucial to acknowledge the constraints and difficulties associated with the implementation of AI and ML in the mining sector. With respect to question Q2, the study provided a detailed analysis of existing expert systems used in the mining industry. We reviewed their main advantages, such as increased prediction accuracy and improved safety at production sites, and identified disadvantages, including high implementation cost and difficulty in integrating with existing infrastructure. This is supported by other studies, such as [62] and [63], where ML algorithms have helped to improve electric locomotive control and mineral mapping. Regarding the third research question Q3, the article illustrates the issues and future directions of AI in the mining sector. In particular, this is the development of more advanced AI algorithms that can cope with complex operating scenarios in multi-agent systems. Additionally, the article highlights the need for further research to gain a comprehensive understanding of the potential benefits and drawbacks of AI and ML in mining industry, establish best practices for their implementation, and explore promising opportunities for combining data and psychological approaches in managing and optimizing mining processes using AI. Despite promising results, findings of the research have certain limitations. First of all, the implementation of AI and ML requires significant financial outlay and availability of quality data, which may be a challenge for some mining companies. It is also worth noting that many technologies are at an early stage of implementation and further work is required to improve and adapt them to the particular requirements of the mining industry, which will be done as part of the grant work. Using advanced AI and ML techniques, the proposed expert system aims to solve critical problems in the mining industry. We also found that prospective research should prioritize the development of more advanced AI algorithms that can handle multi-layered operational scenarios, especially in multi-user environments. In addition, the study revealed the need to develop more robust approaches to integrate data from different sources, which may lead to more robust AI models. The outcomes of the research are consistent with the findings of other works on AI utilizations in mining sector. For example, work [62] showed the effectiveness of reinforcement learning algorithms for driving vehicles, and the study of [63] demonstrated that deep learning can be successfully applied in predicting mineral prospectivity. To fully leverage the capabilities of AI and IoT in the mining industry, it is essential to carry out further research to develop cost-effective solutions that are affordable for both large and small mining companies and to develop interoperable standards to more easily integrate AI technologies into existing infrastructure.

7. CONCLUSION

While the utilization of AI and ML in mining industry offers numerous benefits, several obstacles need to be addressed to unlock their full potential. One of the main problems is the qualitative and quantitative merits of data. The successful fitting of AI and ML models relies on access to substantial volumes of high-quality data, which can often be scarce in the mining industry. Additionally, data may be disparate and inconsistent, making integration and analysis difficult. In the future, it will be important to develop methods for collecting, cleaning and unifying data to ensure its reliability and completeness.

Another significant issue is the complexity of mining operations. AI and ML models must take into account many factors, such as geological conditions, equipment technical parameters and external influences such as weather conditions. This requires the development of more complex and adaptive algorithms that can cope with such complex and variable conditions. Security and reliability are also key aspects to consider when introducing AI and ML into the mining industry. Any errors or failures in the operation of AI systems can lead to serious consequences, including accidents and losses. Therefore, the development of reliable and robust systems that can operate under conditions of uncertainty and provide a high degree of safety is required. Ethical and legal considerations are equally critical in the execution of AI and ML in the mining sector. Ensuring adherence to regulatory requirements and standards while addressing potential societal and ecological impacts is essential. Achieving this requires close cooperation among mining companies, regulators, and society to establish robust ethical and legal frameworks for the use of these technologies. Moreover, there is a pressing need for workforce training to support these advancements. The implementation of AI and ML requires the availability of qualified specialists who can develop, implement and maintain these systems. This requires investment in education and training, as well as the creation of vocational training programs. By focusing on the identified challenges and following suggested future research directions, the mining industry can overcome these barriers and achieve sustainable and efficient operations. Further collaboration between researchers, engineers and AI specialists, as well as the sharing of knowledge and experience between different industries, can contribute to more effective application of AI and ML in the mining sector. Establishing international collaboration is crucial for sharing optimal strategies and creative decisions to expedite the adoption of these technologies and enhance their effectiveness. In summary, the future of AI and ML in the mining sector hinges on linking existing issues as well as persistently pursuing novel approaches. Research and development aimed at improving data quality, developing complex algorithms, ensuring security and reliability, compliance with ethical and legal standards, and training are key areas for the continued enhancement and successful application of AI and ML. In summary, this body of literature review has provided a comprehensive overview of the current applications of AI and ML in expert systems within the mining sector. The analysis highlighted several modern methods and technologies that are instrumental in enhancing decision-making processes, optimizing operational efficiency, and improving safety in mining operations. Key algorithms discussed, including predictive analytics, neural networks, and reinforcement learning, will serve as foundational components in the ongoing project focused on developing an expert system for decision-making regarding the reinforcement and maintenance of mine workings. By leveraging these advanced AI and ML techniques, the proposed expert system aims to address critical challenges in mining operations, ultimately contributing to safer and more sustainable practices in the industry. The insights gained from this review will guide future research and development efforts, ensuring that the expert system is both innovative and effective in meeting the needs of modern mining operations.

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AUTHOR CONTRIBUTIONS STATEMENT

Each author has contributed to the development of the article in the following areas according to the taxonomy of author roles (CRediT) presented in Table:

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Natalya Mutovina	✓		✓			✓		✓	✓				✓	
Margulan Nurtay		✓	✓			✓		✓	✓	✓				
Alexey Kalinin	✓			✓	✓						✓		✓	
Aleksandr Tomilov		✓			✓		✓			✓		✓		✓
Nadezhda Tomilova	✓		✓	✓						✓	✓	✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

Informed consent was not required for this study.

ETHICAL APPROVAL

Ethical approval was not required for this study.

DATA AVAILABILITY

No data was used for the research described in the article.

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BIOGRAPHIES OF AUTHORS

Natalya Mutovina candidate of technical sciences, assistant professor. Currently working at the Abylkas Saginov Karaganda Technical University at the Department of Information and Computing Systems. From 2003 to 2004, she studied for a master's degree in computer science and software, and received a master's degree with honors. In 2019, she received a certificate in the international educational program SCIENCE SLAM KAI. CDAC Certificate, Patna Series of webinars data science and artificial intelligence. Has more than 20 years of scientific and pedagogical experience, publications of articles in the Scopus database. Professor of the Russian Academy of Natural Sciences. She can be contacted by email: mutovinanatalyavic@gmail.com.

Margulan Nurtay master of science. In 2022 he graduated from Karaganda Technical University with a degree in information systems. Currently works at the Abylkas Saginov Karaganda Technical University in the Department of Information and Computing Systems. Has more than 5 years of scientific and technical experience, publications of articles in the Scopus database. Conducts scientific research on artificial intelligence in medicine. Supervises work on conducting scientific research on computer vision with undergraduate students. He can be contacted by email: solano.lifan2@bk.ru.

Alexey Kalinin was born on 1976 in Karaganda in Kazakhstan. In 1998 he graduated from Karaganda Technical University with a degree in electric drive and automation of technological complexes. Qualification-electrical engineer. Honors degree. Doctor Ph.D. (2018). Since 2001, he worked as a senior lecturer at the Department of Automation of Production Processes of the Karaganda State Technical University. From 2019 to the present, head of the Department of Information computing systems of the Abylkas Saginov Karaganda Technical University. The implementation of information technologies for controlling the modes of the large heat supply systems reduces the likelihood of equipment failures and accidents leading to environmental pollution and to the occurrence of the massive man-made disasters. He can be contacted by email: a.kalinin@kstu.kz.

Aleksandr Tomilov doctor Ph.D. Alexander Nikolaevich Tomilov was born on 1987 in Karaganda in Kazakhstan. In 2008 he graduated from Karaganda Technical University with a degree in mine surveying. He has a basic education in the field of IT, he applied knowledge and experience in the development of application software to solve Arcelor Mittal Temirtau problems. Currently works at the Abylkas Saginov Karaganda Technical University in the Department of Information and Computing Systems. Has more than 13 years of scientific and pedagogical experience, publication of articles in the Scopus database. He can be contacted by email: tom44487@mail.ru.

Nadezhda Tomilova Candidate of Technical Sciences, assistant professor. Currently working at the Abylkas Saginov Karaganda Technical University at the Department of Information and Computing Systems. Has more than 40 years of scientific and pedagogical experience, publications of an article in the Scopus database. Professor of the International Academy of Informatization. The implementation of information technologies for controlling the modes of the large heat supply systems reduces the likelihood of equipment failures and accidents leading to environmental pollution and to the occurrence of the massive man-made disasters. She can be contacted by email: tomilova_kstu@mail.ru.