From the industrial revolution to the AI era: transforming safety and efficiency in Jiu Valley mining through intelligent and predictive systems

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Abstract. Since the dawn of civilization, humanity has demonstrated a remarkable capacity for progress. Innovation has been, and continues to be, the bedrock of all the techniques, equipment, and mechanisms that surround us today, aiding us in scientific, medical, and engineering fields, as well as in our daily lives. Significant discoveries were also made in other fields, such as metallurgy, with Abraham Darby's invention of coke-based cast iron and Wilkinson's development of steel rolling. The Industrial Revolution was a complex technical process where manual labor was replaced by machinery. In this mechanized system, the worker's role was to supervise, adjust, and feed the machines, while also performing quality control. The revolution resulted in increased production, urban expansion, and scientific progress.
The current era is characterized by the ability to transmit and access information without the restrictions of the past. This concept is tied to the Digital Revolution, which signifies the transition to an economy founded on the transmission, processing, and storage of information—the Information Age. The concept of inanimate objects being endowed with intelligence dates back to ancient times. For example, the Greek god Hephaestus was mythologized as forging robotic servants from gold, while priests in ancient Egypt used hidden mechanisms to make statues of gods move. Over the centuries, thinkers like the Greek philosopher Aristotle, the 13th-century Spanish theologian Ramon Llull, the mathematician René Descartes, and the statistician Thomas Bayes described human thought processes in symbolic terms, using the tools and logic of their respective eras. These contributions laid the foundation for core artificial intelligence concepts, such as knowledge representation and logical reasoning.

1 The foundations of artificial intelligence development

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The late 19th and early 20th centuries were crucial for the development of computers. In 1836, Charles Babbage and Augusta Ada King (the Countess of Lovelace) conceived the first design for a programmable machine, the Analytical Engine. Babbage created the design for the first mechanical computer, while Lovelace, considered the world's first programmer, anticipated that the machine could do more than simple calculations, being able to execute any operation described by an algorithm.

Progress in computing during the 20th century laid the foundations for artificial intelligence. In the 1930s, the mathematician Alan Turing introduced the concept of a "universal machine" capable of simulating any other machine. His theories were fundamental for the emergence of digital computers and AI. The current period is marked by the rise of generative artificial intelligence, which can create new content (text, images, video, music, etc.) based on user prompts [2].

Although OpenAI released its GPT language model in 2020, the popularity of AI exploded in 2022. The wave began with the launch of image generators Dall-E 2 and Midjourney, culminating in the release of ChatGPT in November. This launch triggered a rapid competition, with rival chatbots like Claude (Anthropic) and Gemini (Google) being introduced. In 2023 and 2024, audio and video generators also appeared (e.g., ElevenLabs and Runway).

While generative AI technology is still in its early stages - with issues like "hallucinations" and the need to find practical and cost-effective applications - these innovations have brought artificial intelligence to the forefront of public attention, generating both enthusiasm and concern [3].

2 The use of artificial intelligence in the extractive industry

AI promotes the economic growth of the mining sector by increasing productivity, optimizing operational costs, and maximizing profitability. However, its potential to advance multi-objective optimization, which involves addressing multiple sustainability goals, has been largely overlooked. To successfully formulate and implement such multi-objective mining strategies, a wide range of diverse data must be collected, processed, and analyzed to optimize the chosen path. Current technological tools fail to capture a comprehensive picture of the relevant data [4].

The application of artificial intelligence in mining can be beneficial in several key areas:

- ✓ Energy Optimization: By leveraging AI and similar advanced technologies, the mining industry can optimize energy consumption. This is achieved by analyzing data to identify energy-saving opportunities, thereby enhancing efficiency.
- ✓ Environmental Data: AI can help reduce environmental impact and workplace risks in mining by analyzing data efficiently and quickly. Specifically, AI can identify areas where operations can be optimized and can factor in the impact on the

surrounding environment. For example, mining leader BHP and tech giant Microsoft use AI and Machine Learning (ML) to boost copper production. They use real-time copper concentration data and Azure Machine Learning to make hourly predictions, which are then used to provide recommendations to the operations team.

✓ Intelligent Geological Exploration: AI assists in mining exploration by analyzing vast quantities of data to identify on-site targets and provide actionable insights. This offers greater efficiency on-site, in terms of both time and cost. Barrick Gold Corporation, one of the largest gold mining companies globally, exemplifies the implementation of AI technologies for mining exploration. The company uses AI algorithms to process geological and geophysical data, which helps identify potential mining sites and optimize drilling operations.

✓ Predictive Maintenance: AI models for predictive maintenance can evaluate variables that reflect the current state of an asset, make predictions based on usage trends, and notify maintenance teams in advance of potential equipment failures. This approach not only ensures enhanced on-site safety for the workforce but also allows companies to plan more efficiently. ABB Global uses predictive maintenance in mining with its ABB Ability Predictive Maintenance service, providing mine operators with easy-to-use, real-time dashboards and reports on the state of key assets, allowing for quick repairs and the elimination of unnecessary maintenance that could pose safety risks. Risk assessments and workplace safety: AI's ability to evaluate and alert to potential risks in mine facilities could revolutionize the industry by creating a more efficient and safer environment for the workforce.

✓ Automation: Automation continues to advance with the introduction of more electric machinery in mining, capable of reaching areas where miners cannot go. In January 2023, the AI-based robotic platform manufacturer Offworld announced orders to implement its industrial AI-based robotic mining systems starting in 2025.

✓ Ore Sorting: AI-based sorting systems can identify valuable minerals from waste rock in real-time, ultimately leading to higher recovery rates and reduced processing costs. Global mining leader Vale launched its first AI center in 2020 in Espírito Santo, dedicated to sustainability and safety. The company uses technology to analyze ore samples and decide on the best sorting methods to maximize mineral recovery, resulting in remarkable outcomes for environmental, health, and safety aspects of the deposit.

✓ Decision Support Systems: AI provides benefits in supporting workers' decision-making, including enhanced worker safety, increased efficiency of previously lengthy processes, and reduced costs. Notably, mining company Anglo American has consistently explored AI applications in its mining operations to become more sustainable and produce less waste. The company developed AI solutions for mineral exploration and resource estimation, helping workers identify the most efficient potential mining sites. AI tools enable companies to make the best possible decisions while ensuring all factors mentioned above are taken into consideration.

3 Possibilities for ai use and application in the Jiu Valley mines

The Jiu Valley, a region with a long-standing tradition in mining, faces significant challenges regarding the safety and efficiency of mining operations. With the rapid evolution of technologies, artificial intelligence (AI) has begun to pave the way for solutions in this field. This work explores the possibilities of using artificial intelligence in Jiu Valley mining, with a special focus on monitoring methane flows, the mathematical calculation of fire indices,

correlating AI results with those of established programs, and modernizing telemetric stations [5].

✓ Monitoring and Calculation of Methane Flows: Methane is a major risk in the mining industry due to its explosive potential. Using artificial intelligence to monitor and calculate methane flows, both absolute and relative, can significantly increase safety in the Jiu Valley mines. AI algorithms can analyze data collected in real-time and predict trends in methane accumulation, allowing for prompt and efficient interventions. This technology could reduce response time in critical situations and prevent accidents caused by uncontrolled gas accumulations.

✓ Mathematical Calculation of Fire Indices: Another critical area where artificial intelligence can bring considerable benefits is the mathematical calculation of fire indices. By using advanced machine learning algorithms, it is possible to achieve a more precise assessment of fire risks. This is essential for preventing disasters and protecting lives and the deposit. AI can analyze multiple factors, such as temperature, humidity, and gas concentrations, and translate them into calculation formulas (Graham's Index, Respiration Index) to provide an exact estimate of the probability of fire and its potential development.

✓ Correlation of AI Results with Established Programs: To ensure the reliability and accuracy of the data, it is essential to correlate the results obtained through artificial intelligence with those provided by established software programs like CANVENT, VentSim, and Ventcraft. These programs are already implemented in many mining operations and provide a solid basis for comparison. Data correlation can lead to better calibration of AI algorithms and their continuous performance improvement.

Modernization of Telemetric Stations: Telemetric stations are crucial for collecting the data needed to monitor mine conditions. Modernizing these stations to meet current technological standards is an essential step in integrating artificial intelligence. New stations should be equipped with modern sensors capable of transmitting real-time data to AI systems. This update will allow for better monitoring of conditions and a faster response to potential dangers.[6].

✓ Monitoring of Gas Concentrations and Explosive Dust Levels: The use of artificial intelligence for monitoring gas concentrations and explosive dust levels is another crucial application area. Based on historical data collected, AI can detect, operate, and anticipate the exceeding of safety thresholds. This allows for a faster and more efficient intervention, reducing the risks associated with the accumulation of explosive dust and gases in the mining environment.

A few ideas focused on and developed from the information presented in this work could look like the following:

3.1 Rapid alert system for methane and explosive dust accumulations

3.1.1 Architecture and system components

To build such a system, we need to understand its key components and how they interact.

IoT (Internet of Things) Sensors: These are the "eyes and ears" of the system. Modern sensors, strategically distributed in critical areas of the mine, continuously collect real-time data. The necessary types of sensors would be:

- Methane (CH_4) sensors: Measure concentration in volume percentage or as a percentage of the LEL (Lower Explosive Limit).
- Dust sensors: Detect explosive dust particles, often relying on laser light scattering technology.

- Environmental sensors: Measure factors like temperature, atmospheric pressure, humidity, and airflow. This contextual data is essential for AI algorithms.
- Communication Network: Data collected from the sensors must be transmitted quickly and reliably to a central server. In the underground environment, specialized wireless networks (such as Wi-Fi Mesh or LoRaWAN) are preferred because they ensure extensive coverage and low power consumption.
- Artificial Intelligence (AI) Module: This is the "brain" of the system. It runs on a local server or in the cloud and processes the data.
- Historical Database: Stores all data collected by sensors over time. This massive dataset is used to train the AI models.
- Machine Learning (ML) Algorithms: This is where the intelligent part comes in. For predicting accumulations, time-series models like Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) are excellent at identifying patterns in sequential data. These models can learn how gases and dust behave based on environmental conditions and mining activity [7].
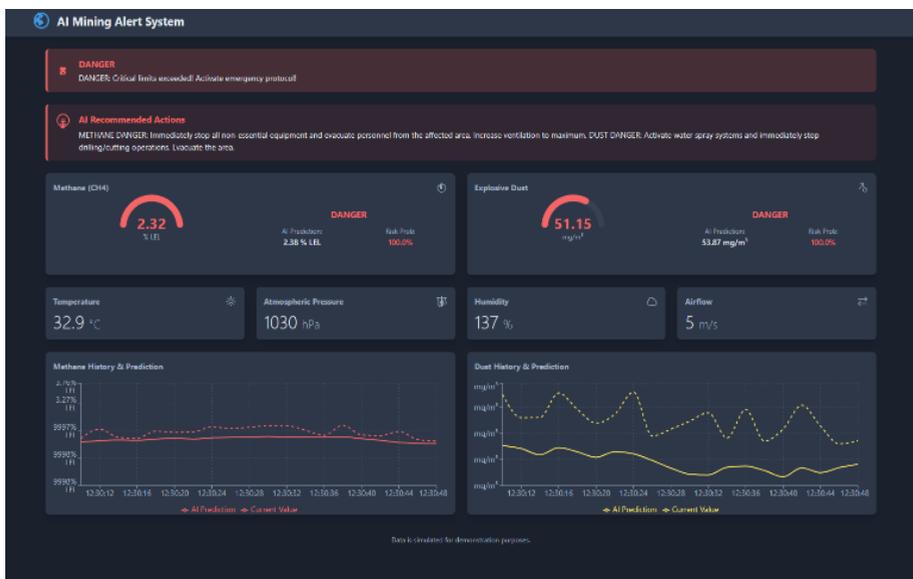

Fig. 1. Example of interface of a Monitoring and Prediction System for methane and explosive dust accumulations

3.1.2 Operation flow and logic

The system not only monitors but also acts, following these main steps:
- Data Collection: Sensors send data to the server at regular intervals (e.g., every 1-5 seconds).
- Real-time Analysis: The AI module takes this data and compares it to learned patterns.
- Risk Prediction: The AI calculates the probability that a certain concentration will reach a critical threshold (e.g., 2%) in the next 15-30 minutes.
- Alert Generation: If the prediction exceeds a certain risk threshold, the system triggers an early warning, before traditional sensors reach the critical alarm level. The alert can be sent through various channels:
- Notification on a digital dashboard.
- SMS or email to responsible personnel.

- Light or sound signals in the hazardous area.
- Action Recommendations: The system can also provide automated recommendations, such as stopping activity in a specific area or adjusting the ventilation flow to prevent accumulation.
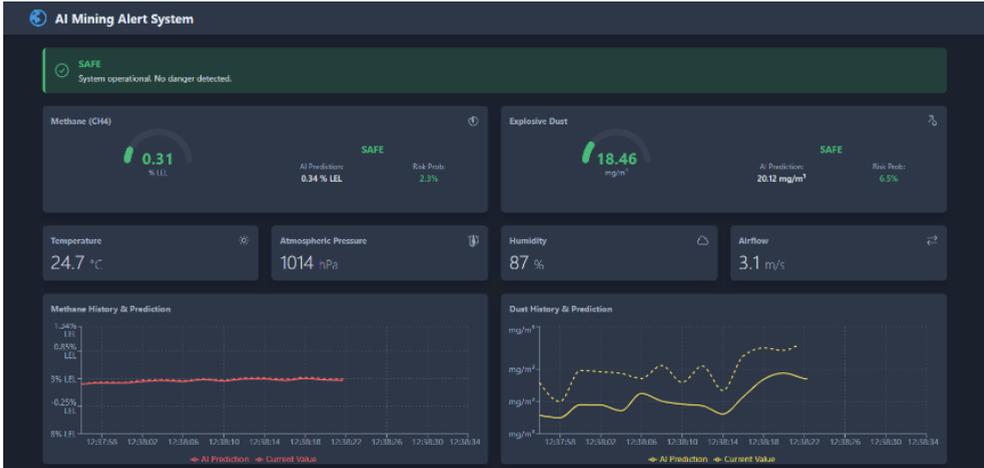

Fig. 2. Example of interface of a Monitoring and Prediction System for methane and explosive dust accumulations

3.1.3 Benefits and competitive advantages

The most important benefit is enhanced safety: The system prevents incidents through early warnings, giving personnel valuable time to evacuate or intervene.
Operational optimization: By correlating data with the work schedule, the AI can identify the safest times for certain activities, reducing downtime [9].

Predictive maintenance: Another AI application. By analyzing sensor data, the system can detect a potential fan or ventilation duct failure long before it happens.

Reduced costs: Preventing a single incident can save millions of euros. Furthermore, by optimizing ventilation, energy costs—a major expense in mining operations—are reduced.

3.1.4 Challenges and next steps

Implementing such a system is not without challenges.

Data quality: AI models are only as good as the data they are trained on. Precise sensor calibration and the collection of a vast, high-quality dataset that covers a variety of operational conditions are crucial.

Modeling complexity: A model must account for many factors: the geometry of the galleries, variations in temperature and pressure, airflow direction, and the type of mining activity.

Integration with existing infrastructure: The system must seamlessly integrate with existing telemetric stations and ventilation equipment.

A project of this kind should start with a pilot study in a small area of the mine to validate the AI model and demonstrate the benefits before it is expanded to the entire operation.

3.2 AI assistant for fire risk assessment

This is a critical area, given that underground fires can have catastrophic consequences. An AI-based system would revolutionize how risk is calculated and managed, overcoming the limitations of traditional methods.

3.2.1 Traditional vs. intelligent fire risk assessment

Classic fire risk assessment methods rely on gas analysis in the mine atmosphere using predefined indices, such as Graham's Index or the Respiration Index. These indices provide a "snapshot" of the current state but do not account for the self-heating processes that are at the root of endogenous fires.

An AI system overcomes these limitations through the dynamic correlation of multiple variables, allowing not just for an assessment but also a prediction of risk, focusing specifically on the phenomena that lead to endogenous fires [10].

3.2.2 Data integration for endogenous fires in the AI system.

To detect an endogenous fire in its nascent stage, the AI system must collect and process specific data. In addition to gas and environmental sensors, the system will include:
- Temperature sensors: Placed in high-risk areas, these sensors detect micro-increases in temperature.
- Air composition analysis: An increase in the ratio of carbon monoxide (CO) to oxygen (O_2) is a key indicator of slow oxidation. The AI system continuously monitors these ratios.

Geological and operational data:
- Coal composition: Coal with a higher tendency for oxidation will be flagged as a high-risk area in the system.
- Extraction front speed: A slow or stationary extraction pace can favor the accumulation of friable coal and, consequently, self-heating.
- Air circulation: An optimal airflow is essential to dissipate heat. The AI will compare the actual airflow with the optimal one to identify areas with deficient ventilation.

3.2.3 Operation flow: from data to prediction

The AI system will run on a central server and use Machine Learning algorithms to build a "signature" of endogenous fires.

The AI algorithm takes data from all sensors. Instead of calculating simple indices, it analyzes complex patterns. For example, a constant, even minuscule, temperature increase over 24 hours, combined with a decrease in O_2 in an area with a specific type of coal, can be an alarm signal for self-heating.

Based on the identified patterns and historical data, the AI calculates a probability of risk for each section of the mine. This is no longer a simple alert but a prognosis, allowing personnel to intervene preventively.

The analysis results are displayed on a digital map of the mine. Areas with an increased risk of endogenous fire are highlighted in colors, allowing for immediate visualization of the danger. Detailed alerts, which include the probable cause (e.g., self-heating) and action recommendations, are sent to personnel.

Practical applications and benefits regarding the prevention of endogenous fires include:
- Early intervention can extinguish the fire in its incipient stage, thus preventing a disaster.

- By identifying high-risk areas, companies can adjust their extraction plans to avoid coal accumulation in those sectors.
- The AI system provides a scientific justification for safety decisions, helping to comply with regulations and create a safer working environment [11].

3.3 Deepening data quality for AI models

AI models are only as effective as the data they are trained on. A simple mention of "high-quality data" is not enough. To ensure the system's accuracy, we must define exactly what this means:

- Granularity (Temporal Resolution): Data collection must be frequent enough to capture the rapid dynamics of the mining environment. A resolution of 1-5 seconds for sensor measurements of gas, dust, and temperature is ideal. A lower resolution (e.g., every minute) can mask concentration spikes or fluctuations that foreshadow an incident.
- Data Volume: An AI model needs a vast and representative dataset. A history of at least 6-12 months of continuous data is necessary to cover seasonal variations, different mining scenarios, and a wide range of environmental conditions. This large volume of data allows algorithms to identify subtle and rare patterns, such as those that lead to an endogenous fire.
- Data Accuracy and Fidelity: Each data point must be precise and reliable. This is achieved through regular and rigorous sensor calibration. Any erroneous value or "noise" in the data can lead to false predictions or an underestimation of risk. Furthermore, the data must be temporally synchronized so that a temperature increase can be accurately correlated with a gas concentration increase.
- Data Labeling: To train a predictive model, it's essential that historical data is "labeled." This means that every real incident (e.g., methane accumulation, self-heating, mini-fire) must be marked in the database with the exact time and location. This labeling process allows the model to "learn" what data patterns precede a dangerous event.
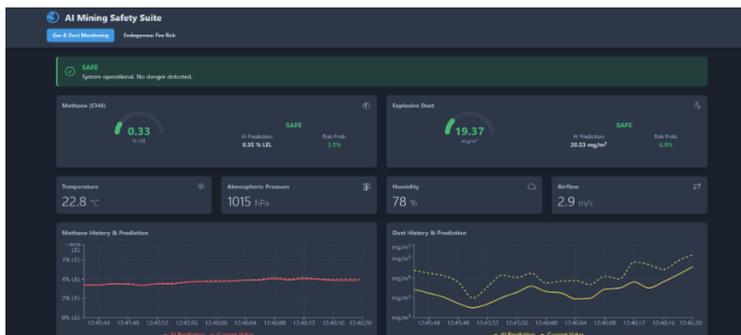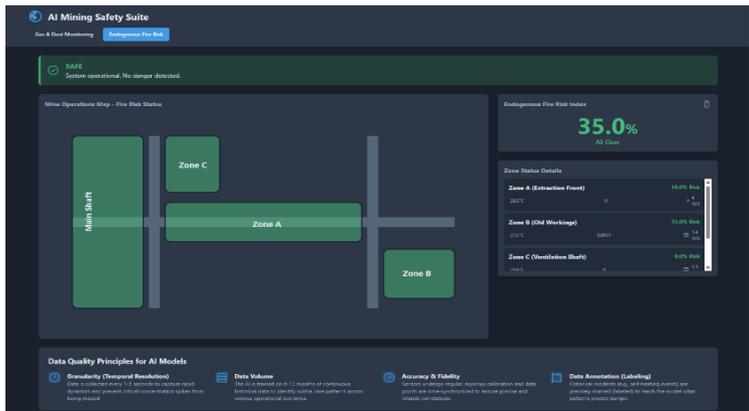
Fig. 3. Example of interface of a Monitoring and Prediction System for fire prevention.

3.4 Technological validation and scientific rigor

To demonstrate that the AI system's predictions are reliable and superior to traditional methods, a rigorous validation methodology is essential [12].
- Data Splitting: Before starting training, the historical dataset is divided into three subsets:
- Training set (~70-80%): Used to "teach" the model.
- Validation set (~10-15%): Used to tune the model's parameters and prevent overfitting.
- Test set (~10-15%): This is the most important set for validation. It is a dataset unseen by the model, used to evaluate its final performance. If the model has high accuracy on this set, it means it is capable of generalizing and making correct predictions under real conditions.
- Cross-Validation: A more advanced technique, useful for smaller datasets. The dataset is divided into k subsets (usually 5 or 10). The model is trained on k-1 subsets and tested on the remaining subset. This process is repeated k times, ensuring that the model's performance does not depend on a random data split.
- Confusion Matrix: To evaluate performance, precise metrics are used, such as:
- Accuracy: How often the model was right.
- Precision: How many of the given alerts were correct. Low precision would lead to false alarms, which would undermine trust.
- Recall: How many of the actual dangerous events the model succeeded in detecting. A high value is critical for a safety system.

3.5 Economic and implementation aspects: a cost-benefit analysis

A credible work must justify not only the technical feasibility but also the economic viability of the solution.
Cost Component: A detailed analysis should consider the following costs:
- Initial investment (CAPEX): The cost of advanced sensors (hardware), network infrastructure, servers, and software licenses for the AI platform.
- Operational costs (OPEX): Periodic maintenance, sensor calibrations, energy consumption, and the salaries of specialized personnel for managing and interpreting the system.
- Benefit Component: The benefits must be quantified as much as possible:

- Reduced operational costs: Significant savings from optimizing the energy consumption of ventilation systems, thanks to AI recommendations. An estimate could be 15-25% of the annual energy costs for ventilation.
- Reduced downtime: Preventing major incidents avoids long-term operational shutdowns, which can cost tens or even hundreds of thousands of euros per day.
- Predictive maintenance: Early detection of malfunctions reduces repair costs, prevents major breakdowns, and lowers the risk of using faulty equipment.
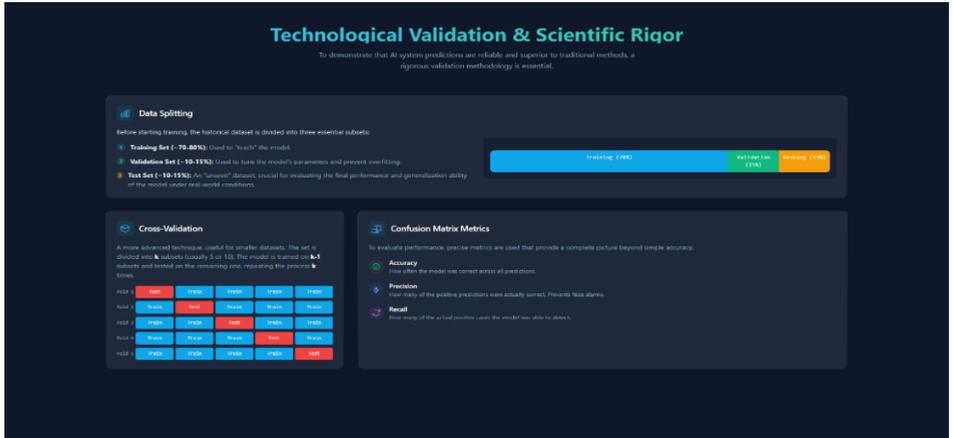

Fig. 4. Economic and Implementation Aspects: A Cost-Benefit Analysis

4 Conclusions

✓ The work offers a profound and convincing analysis of artificial intelligence's potential in the mining industry, transforming a theoretical concept into a practical and viable solution proposal. By integrating the history of technology with concrete applications for the Jiu Valley mines, the work demonstrates that AI is not just a tool for automation but a catalyst for a fundamental paradigm shift, from a reactive work environment to a predictive and proactive one.

✓ Considering its scientific and practical rigor, the work goes beyond a simple description of AI's benefits by including detailed sections on data quality and validation methodologies. This is evidence of scientific rigor, showing that the project's success does not depend on simple assumptions but on a systematic approach. It correctly highlights that the accuracy of predictions depends on a large data volume, fine temporal resolution, and rigorous sensor calibration. The mention of techniques like data splitting and the confusion matrix lends credibility and places the work at the level of an advanced technical proposal.

✓ The economic relevance and justification of the investment establish that the cost-benefit analysis, though concise, is essential. The work doesn't just list benefits; it also quantifies them, providing an estimate of energy savings and reduced operational costs. By directly linking the initial investment (CAPEX) and operational costs (OPEX) to financial benefits, a strong argument is built for mine management. The prevention of a single major accident or an endogenous fire fully justifies the investment, demonstrating that AI is not a cost but a strategic investment in safety and profitability.

✓ The most important conclusion is that AI has the potential to revolutionize safety in mining, especially regarding endogenous fires, a complex problem that is difficult to manage with traditional methods. The proposed system shifts from passive

monitoring to risk prediction. By analyzing subtle correlations between various variables (temperature, gases, airflow), the AI can detect self-heating processes at an incipient stage, long before classic sensors would trigger an alarm. This capacity for preventive intervention, based on a scientific prognosis, represents a major evolution for the mining industry in the Jiu Valley.

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