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THE PRESENT AND FUTURE PROSPECT OF ARTIFICIAL INTELLIGENCE IN THE MINING INDUSTRY

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Abstract:
The mining operation uses traditional and conventional techniques to extract minerals. Besides extracting minerals some other auxiliary operations are expedient to have safe and economical process. Presently some mechanical and electronics equipment have been used in this regard. Some softwarehas also been developed to serve the purpose. But these are not sufficient to meet the requirements of day by day changing scenario of introduction of newer and advanced technology. To keep up with the new technology modernization and the profit in shake of investors and stakeholders and importantly for the nation, and to ensure health and safety mining industry needs to approve new-age autonomous technologies and intelligent system in their field. Integration of Artificial Intelligence, Machine Learning, Internet of Things (IoT) and Automation are the keys to the 4th revolution in mining industry.In this way Artificial Intelligence can replace these technologies as the former is the simulation of human intelligence processes by machines, especially computer systems. The present paper focuses on the present and future of AI in mining industries.AI systems work by ingesting large amounts of labelled training data, analysing the data for correlations and patterns, and using these patterns to make predictions about future states. The present era is of AI which can have wider applicability in the various auxiliary operations associated with mining work. Owing to its performance better than human beings its future prospect will be of better importance.

Keywords:
Artificial Intelligence, Deep Learning, IoT in Mining, Machine Learning, Mining Automation, Mining Industry

1.Introduction:

Mining is considered as one of most required industries in 21st century as it is the supplier of raw materials to other industries. Mining operations involve extraction of ores and minerals of various kinds from the earth, which cannot be produced in laboratory or by cultivation. Although being one of the most profitable sector mining industries is one of the riskiest investments because of dangers associated with operations particularly at deeper underground mines. Mining industries are continuously facing issues related to capitals, infrastructure, health and safety and most importantly environmental and geological consequences. Mining provides employment opportunities and performs a lead role of a country’s economic development with systemic governance. In general, there are four basicmethods of mining:
(i) Surface Mining for shallow depth ore bodies, (ii) Underground mining for deep or deposits, (iii) placer mining for extract valuable metals from sediments of beach or river beds, (iv) In-situ mining, the method of recovering minerals from earth without extracting the mix of rocks and ore to the surface for processing.
Artificial intelligence is the science of making machines that can think like humans. It can do things that are considered "smart." AI technology can process large amounts of data in ways, unlike humans. The goal for AI is to be able to do things such as recognize patterns, make decisions, and judge like humans. Artificial intelligence systems work by using any number of AI techniques.

Machine Learning: A machine learning (ML) algorithm is fed data by a computer and uses statistical techniques to help it "learn" how to get progressively better at a task, without necessarily having been programmed for that certain task. It uses historical data as input to predict new output values.

Deep Learning: Deep learning is a type of machine learning that runs inputs through biologically inspired neural network architecture. The neural networks contain a number of hidden layers through which the data is processed, allowing the machine to go "deep" in its learning, making connections and weighting input for the best results.

Neural Networks: Neural networks are a series of algorithms and a subset of machine learning that process data by mimicking the structure of the human brain. Each neural network is composed of a group of attached neuron models, or nodes, which pass information between each other.

Natural Language Processing: Natural language processing (NLP) is an area of artificial intelligence concerned with giving machines the ability to interpret written and spoken language in a similar manner as humans. NLP combines computer science, linguistics, machine learning and deep learning concepts to help computers analyse unstructured text or voice data and extract relevant information from it.

Computer Vision: Computer vision is a field of artificial intelligence in which machines process raw images, videos and visual media, taking useful insights from them. Then deep learning and convolutional neural networks are used to break down images into pixels and tag them accordingly, which helps computers discern the difference between visual shapes and patterns. Computer vision is used for image recognition, image classification and object detection, and completes tasks like facial recognition and detection in self-driving cars.

2. Reasons for Adoptability of AI in Mining Industries and Operations:

In brief expected reasons to adopt AI are:

1. AI provides fast and accurate on-site decisions reducing the errors.
2. Using AI ensures consistent and radially efficient method for making accurate and quick assessment of potential risks.
3. AI should manage and process large amount of data (big data) with speed, accuracy and efficiency.
4. Boosting efficiency by increasing consistency and quality work that typically is subject to human error.
5. Ensures improved health and safety measures.
6. Increased resource throughput.
7. In long run of efficient use, it can reduce the operation cost.
8. Better utilize the equipment, machines and vehicles.
9. Accelerating the shift to be more "process and continuity rather than people-oriented".
10. Operation timing and product quality enhanced.
11. Reduce energy demand with increasing efficiency of whole operation.
12. Using neural network, the machine or software could learn the characteristics that the operator is looking for.
13. AI enhanced automated system using integrated process control assists with significant energy cost and production cost reduction.

3. AI and Automation in Mining:

3.1 Open Pit Fleet Management System

Increase Haulage Efficiency using Intelligent Dispatch:

An intelligent Dispatch System allows mine Dispatchers to improve routing and run their mine on auto-pilot. Advanced AI based algorithms use real time loading and haulage performance data at each loading point to dynamically allocate Haul Trucks to Shovel/Front Wheel Loaders so mines can:

Maximize tons hauled every shift

Minimize wait times at loading units

Decrease traffic congestion
Increase haulage efficiency
These results in a dramatic reduction of shovel and haul truck queuing time and increase in Productivity and Overall Equipment Effectiveness.

GPS and Telematics based Automated Trip Cycle Analysis
Increase Situational Awareness and Operator Safety
Proximity Detection and Collision Avoidance
Streamline shift changes, re-fuelling and breaks
Manage Stockpiles

3.2 Automated Drillers and Intelligent Drilling Systems:

Drilling and blasting are the two fundamental operations of every mining project. Holes are drilled into any rock or hard surface to fill them with explosives. Blasting the explosives induce cracks in inner geology of the hard surface or rock. Typically, a drill cycle involves trimming hole, levelling jacks, drilling holes, cleaning and repeating the process. Instead of doing it all manually, in the automated process the automated drill moves hole to hole following the pre-fitted location coordinates (determined through GPS receivers or based upon any other spotting technique). Sensors might help the machine to predict the environment and the rock type. The whole orientation is also pre-programmed by facilitator.

Drones: Drones with highly efficient cameras could provide real time aerial footage and 3D maps of the site. These data could be used to instantly estimate cumulative measurements, real-time tracking and safe-guarding of equipment's and employees' locations and tracking safety-environmental observances. Deploying drones not only ensures less cost for surveying but also great accuracy and detailed survey. Using data from the drones selecting areas for stockpiling and selecting potential exploration corridors are easy to determine.

3.3 Inspecting Robots:

Remote-control, semi-automated or automated robots are likely to be used in various applications on a mining site. Underground mines have high roof fall or poisonous or flammable gas related risks. Robots may be engaged into dangerous tasks rather than humans on field or underground. Robot also could assist miners by adding light, vision, auditory and vibration or gases sensing capabilities.

3.4 Safety and Accident Analysis:

Mining is a risky and hazardous job. Monitoring the environment and other parameters is a proven way to analysis the accidents and ensure safety, but using AI, prediction of accidents and safety factors would be easy and accurate.

3.5 Environment Monitoring

Using IoT(Internet of Things) and AI, mine environment can be monitored in details.[21-24] the whole system can check the environmental factors using IoT sensors, report after computing the risk using A.I. algorithms and alert in form of alarm with LEDs and alarms in case of emergency. Automatically underground environment factors like different gas levels, smoke, temperature, humidity, light, pressure, dust con-centration etc. Mines, especially underground mines have many types of gases which could be poisonous for human beings and could be flammable and dangerous. Naturally at first the gases (CH_4, NO_2, CO_2, SO_2, NH_3, smoke etc.), present at the mine might be measured using IoT sensors.

3.6 Predict Dust Concentration:

Open cast or open pit mines cause a massive amount of dust and particulate matter emission in open environment. Even in underground mines dust concentration level monitoring and maintaining is an important challenge. ANN type complex intelligent systems can be designed to predict dust particles [26] including particulate matters of different diameters concentration near mine location using meteorological parameters (rainfall, temperature, wind speed, cloud cover, dispersion factor etc.), geographical parameters(distance of receptor from the source with respect to air directions) and emission rate(drilling, loading, conveying, hauling, transporting, unloading etc.).

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3.7 Personal Tracking and Monitoring:

Miners' job is undoubtedly risky. Tracking their positions and conditions around them is live saving in practical cases. It would help to warn and take important steps quickly against any type of possible risk on any worker.

3.8 Roof Support Monitoring

Roof fall is the leading cause of coal miner injuries [30]. Analysing the data received from roof support system of the mine using IoT sensors could be the key to predict hazards like roof fall, water inrush, and release of hazardous gases from the walls etc. For developing a full working roof support monitoring and hazard prediction the following type of data need to be collected: [31]

1. Load on the legs (horizontal downward load)
2. Convergence of the sidewalls
3. Humidity (to predict water inrush)
4. Temperature
5. Gas Detection

Collecting these data using various sensors and equipment's and using these data on pre-trained ANN or machine learning network upcoming hazards could be detected. ML can easily predict the roof support risk and requirements using experience from past data.

3.9 Rockburst Prediction:

For high-stress mines rockburst is a severe disaster. Spontaneous and violent failure of rock structure in high-stress mines is known as rockburst. Traditional rockburst techniques are long-term predictions and short-term predictions.

During the project designing stage long term rockburst prediction is used to predict the risks to operate on the specific site. Common machine learning and deep learning methods [35] that show highest accuracy, are artificial neural network (ANN), distance discriminant analysis (DDA), support vector machine (SVM), Bays discriminant analysis (BDA), Fisher linear discriminant analysis (LDA) etc.

3.10 Slope Stability Analysis:

Stability of mine dumps or stockpiles or open pit slopes is an important parameter of safety and efficient working. To foresee accidents due to slope stability imbalance, modern miners need to use machine learning approaches for achieving reliable and objective evaluation with great accuracy. Proposed models of analysing slope stability depend upon discrete and continuous functions and variables. Some tested [36] machine learning models are support vector machine (SVM), FCM, K-means etc.

3.11 Fly rock analysis and Blasting Pattern Analysis:

The most hazardous event as the consequence of blasting operations is fly rock. Imperfection of blasting pattern design, blasting material or stemming is main reason of flyrock that could endanger lives and equipment's on site. Fly rock analysis is complex and uncertain. Various parameters and unknown relations cause large inaccuracy in empirical models of flyrock analysis. But some of the proposed and tested machine learning models already shows high accuracy to flyrock events [37-41]. As a result of improper blasting pattern undesirable phenomena such as flyrock, poor fragmentation, back break, ground vibration etc. take place. So, recognising right blast pattern is an important job for a mining engineer. ANN for forecasting the peak-particle velocity for the blast-induced ground vibrations is studied by [42-44].

3.12 Subsidence Risk Analysis:

Gradual downward shifting or sudden sinking of ground surface is termed as subsidence. Constructions of mines face many geo-mechanical uncertain challenges when it starts production. Subsidence risk is one of them. Rock mass structure, rock energy density, rock mass drainage, nearby aquifers etc. consider being responsible factors for subsidence construction in proposed machine learning models. Some tested machine learning models for subsidence risk analysis include failure model and effect analysis (FMEA), fuzzy inference system (FIS), ANNs, multilayer perceptron network (MLP). [48, 49]

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3.13 Ventilation:

Mine ventilation system consumes the most amount of energy in case of under-ground mines. Ventilating system must work with highest capacity and efficiency, so the maintenance of ventilation equipment's also cost lots of capital.

AI enhanced smart ventilation system would have:

1. Smartly automated control airflow according to the workflow of the mine.
2. Air flow could be customized according to the need.
3. Associated environmental monitoring system would be a perk.
4. Fail-safe architecture to ensure ventilation in emergency.
5. Blast gas clearing facility associated with ventilation would make the opera-tion safer.
6. Must have an open architecture for easy and quick installing and repairing.

Smart ventilation system would help to (i) save energy cost and capital investment, (ii) make smaller environmental and carbon footprint, (iii) ensures health and safety.

For example, Shift Inc.9 have made an AI enhanced automated adjustable ventilation system for mines with integrated process control assist, open architecture, fail-safe system and environmental monitoring system.

4. Challenges to Implement AI in Mining Industry and Beyond:

Although application of AI and autonomous technologies in mining is almost decades old (started with autonomous trucks), the pace of implementing is painfully sluggish. [101]

1. Implementing AI and autonomous system requires huge initial capital.
2. AI or autonomous technologies do not guarantee instant return for stakeholders.
3. Traditional mining industry has inadequate infrastructure.
4. In fear of losing jobs former workers and supervisors may resist the pace.
5. Industry culture is also resisting the pace as mining corporates still don't sure about the systemized approach to implement AI or automation in industry.
6. Even the AI researchers are not certain about the impact of AI on jobs, economics, working relations, social system and societal makeup.
7. There is risk and uncertainty about unknown behaviours of AI and autonomous systems.
8. It is still not clear about how AI could take group decisions on its own.
9. Functions of most of the AI or automated devices are too complex and need high professional effort to implement.
10. For a well automated mine large number of connected devices will generate large amount of data which will make computing and validating complexities for computers.
11. Many times getting regulatory approval is a serious issue.
12. For AI or automated mining industry lots of miners with traditional and advanced tech-skills are required.
13. Often poor testing data and methods are used for generating insights which lead to noise and over-fitted models.
14. Most AI based technologies are considered as lab-based (not ready for market). So, implementing them is considered risky for the industry.
15. Declining availability of high-grade ores and mineral resources impending large investment is discouraging.
16. As mining industry is considered as a risky undertaking with investment volatility, uncertain grades and variable mineral or ore prices, the industry always preferred proven methods of operation to cut down the risk factor.

For correct implementation of AI in mining, industry needs to follow a series of well-defined steps in designing new technologies and implementing them.

5. Conclusion:

According to the World Economic Forum the calculated investment on digital initiative would be $420 billion in the next decade. Artificial intelligence is also going to save a lot of cash flow and lives in the coming years in mining. "Mining is not everything but without mining everything in nothing" (Max Planck). Mining sector plays a very important role in economic development (neglecting the resource-curse hypothesis concept, which pretty much depends upon the governance). So, with right governance and expect planning artificial intelligence is undoubtedly going to be one of the keys to unlock the full potential of mineral extraction and to ensure safety of workers. But the introduction of AI in mining sector may lead to unemployment in the country like India where vast population resides because of loss of job in mine working. So, a balance must be struct between human work and automated work in mining industry to serve a better environment. The future may be a place of conflict as large number of workers can lose their job. The mine planners will have to take reasonable steps to avoid such type of unwanted situations.

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